Essays in Empirical Macroeconomics: Applications to the GCC Monetary Union

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Submitted to the graduate degree program in Economics
and the Graduate Faculty of the University of Kansas
in partial fulfillment of the requirements for the degree
of Doctor of Philosophy

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Acknowledgement

I would like to take this opportunity to acknowledge and extend my heartfelt gratitude to the following persons who have made the completion of this dissertation possible. Professor Shu Wu not only served as my co-chair but also encouraged and challenged me throughout my dissertation process. He taught me how to be an independent researcher. Professor Ted Juhl, my co-chair, was always there to extend his help. Throughout my academic program, he taught me how to transform any theoretical questions into applied work. Both Professor Shu and Professor Ted guided me through the dissertation process by not accepting any less than my best efforts.

Besides my advisors, I would like to acknowledge the rest of the committee members: Professor William Barnett, Professor Bozenna Pasik-Duncan (from the mathematics department), and Dr. Fernando Delgado (at the International Monetary Fund) who provided insightful comments and encouragement throughout the dissertation process. I thank them all.

During my academic program, I was supported financially by the Saudi Arabian Monetary Agency (SAMA). I am grateful for their support and encouragement.

Last, but not least, I am grateful for all of my family, especially my mother who is always beside me and encourages me by teaching me not to be satisfied with any work that is not perfect, and my father who was always proud of me for being able to go to graduate school. Unfortunately, he passed away one year before I completed my PhD program. I am also grateful for my sisters and brothers who always stood beside me to provide any kind of support whenever it was needed. I dedicate this work to my lovely wife Asya and my children Mohammed and Toqa.

Abstract

With the introduction of the monetary union and the single currency in the Gulf Cooperation Council by 2010, the prospective supernational monetary agency will conduct a single and indivisible monetary and exchange policy. Its policies will be based on the *GCC-wide* economic and financial developments. In this dissertation, I present some empirical tools that can be utilized by the policymakers at the supernational monetary agency to conduct a sound monetary policy.

Policymakers at the GCC supernational monetary agency will be scrutinizing a large number of economic variables in order to obtain a clear signal about the current and future state of the GCC economies. Since economic data is controlled by different agencies, not all economic variables are released simultaneously. In contrast, policymakers will have to make a decision without all of the information available to them yet. To overcome this problem, the second chapter extracted a timely single coincident index that closely track the business cycle evolution of the GCC area by utilizing the Generalized Dynamic Factor Model (GDFM). As by product of utilizing GDFM, each variable in the dataset is classified as pro-cyclical or counter-cyclical with respect to the coincident indicator. The GDFM then categorizes the direction of each variable against the coincident indicator as lagging, coincident, or leading. Since common shocks from any factor models are statistical shocks, the proposed test by Bai and Ng (2006) was applied to the GCC dataset to test the economic meaningfulness of the statistically latent factors.

Recently, central banks have started to utilize large-scale models based on New Open Economy Macroeconomics (NOEM) approach, where the parameters have structural interpretation. Chapter 3 layout a Dynamic Stochastic General Equilibrium Model (DSGE) for a small open economy a with fixed exchange rate regime on the GCC area. It is a small open economy model with some nominal and real frictions. The model can be used by the policymakers at the prospective supernational monetary agency to examine the dynamic effects of exogenous shocks on endogenous macroeconomic variables and understand the sources of business cycle fluctuations in

the GCC area. Also, the derived model can also serve as a tool for policymakers in assessing alternative scenarios in order to conduct a sound monetary policy at the regional level.

Finally, the need for producing accurate forecasts of the key macroeconomic variables has become crucial for both policymakers and economic agents. In a "rich-data environment," where information is scattered over a large number of economic time series, it is not feasible to estimate the forecasting equation of any target variable with all relevant variables. Chapter 4 generates short-term forecasts of key macroeconomic variables for the GCC area in a "data-rich environment" by utilizing different factor models. The ultimate goal is to measure the efficiency gain from using the dynamic factor model of Forni *et al.* (2005) versus the static factor model of Stock and Watson (2002a, b). Since the previous two models are not comparable, I propose two approaches to make the forecasting equations of those two methods more comparable.

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Chapter 1: Introduction

In this introduction, I first give a historical background of the Gulf Cooperation Council (GCC) area. I also discuss the GCC area in the context of the global economy and review the economic convergence within member states of the GCC area. I then outline the essential motivations and research objectives of this dissertation.

1 Characteristics of the GCC Area

1.1 Historical Background

In May 1981, the six Head of States of Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates signed the charter of "Cooperation Council for the Arab States of the Gulf," later to be known as the Gulf Cooperation Council (GCC). The charter lays down the rules and functions of the Supreme Council (formed of Head of States), the Ministerial Council, and the Secretariat-General. In November 1981, just a few months after the establishment of the GCC, the Supreme Council adopted the "Unified Economic Agreement." The agreement went into effect in January 1982. It calls on the member states to coordinate their monetary, financial, and banking policies in an endeavor to establish a single currency in the future. It also calls for establishing a Free Trade Zone. Even though the Free Trade Zone came into force in 1983, little progress had been made toward achieving a full economic integration until the late 1990s.

In December 2001, the Supreme Council ratified the new "Economic Agreement between the GCC States." The new agreement replaced the "Unified Economic Agreement" by encouraging the member states to move from the coordination stage to the harmonization and integration stage. It also draws an ambitious road map for the creation of a common market and a monetary union. The timetable of the new agreement calls for the establishment of a custom union by

2003, convergence criteria by 2005, a common GCC market by 2007[1], and a single currency by 2010.

1.2 The Importance of the GCC Area in the Global Economy

The GCC area is an important region in the global economy for several different reasons. First, it accounts for 45% of proven global oil reserves, and 25% of global natural gas reserves. The GCC area produces 22% and 6.5% of global oil and gas output, respectively. Second, table 1.1 shows the aggregate GDP for the GCC area was $482 billion in 2003. It is expected to grow to $790 billion and $883 billion in 2007 and 2008, respectively[2]. The average real GDP growth for the GCC area has been 7% for the last few years. According the International Finance Corporation (IFC) estimates, the GCC area investment outside its borders is almost $1 trillion as of end of 2006, and it earns $60 billion to $100 billion a year on those investments. Moreover, projects under implementation or planning worth more than $1 trillion in the GCC economies. Finally, as of the end of 2006, the GCC area comprises 35.1 million inhabitants with 40% of them younger than 15 years old. Therefore, the prospect for the future growth in the GCC area is high as sustained oil demand is expected to continue at least over the short-to-medium run horizon and as enhanced structural reforms in the education and training sector are expected to provide employment opportunities for GCC citizens in the private sector. The GCC area will also play an important role in the global imbalances with its current account surplus running around 30% of GDP as of 2006.

1.3 Economic Convergence

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[1] On December 4th 2007, the Head of States agreed to launch the region as a common market by January 2008. This will allow the GCC nationals to have the same right in the employment, education, financial, economic, and residency anywhere in the GCC area.

[2] IMF staff estimates.

As the GCC area adopts a single currency in 2010, the prospective supernational monetary agency will base its monetary policy on the *GCC-wide* economic developments. To achieve an optimal monetary policy, it is important that the GCC economies are not hit by asymmetric shocks. Therefore, economic convergence among the GCC economies is crucial not only in the run up to adopting a single currency, but also after establishing the monetary union. Economic convergence can be defined in terms of monetary, fiscal, and real convergence.

1.3.1 Monetary Convergence

Monetary convergence refers to harmonization of economic variables related to monetary policy such as interest rates, inflation, and exchange rates. Figure 1.1 shows the interest rates of the GCC economies and U.S. Only few years after the inauguration of the GCC area in 1981, the figure shows clearly the high degree of comovement among the interest rates in the GCC economies. The interest rate convergence reflects the convergence in both the inflation and exchange rate's stability in the GCC area as implied by the Uncovered Interest Parity (UIP). Since the GCC economies have a long standing de facto peg with the U.S. dollar, the interest rates closely track the movement of the U.S. interest rate that demonstrates the creditability of the exchange rate peg regime in the GCC economies.

Since 1985, the inflation rates in the GCC area have been low and comove with each other with few exceptions (Figure 1.2). In the early 1990s, Kuwait had a higher inflation rate due to re-construction projects after the Iraqi invasion. Similarly, Qatar experienced a high rate of inflation in the mid 1990s due to massive projects in the natural gas sector. Overall, the inflation convergence over the last two decades in the GCC area is remarkable when compared to what the EU experienced before forming its monetary union 1999. There are some factors that can explain the stability and comovement of inflation rates in the GCC area. First, since all the GCC member states have been supporting the de facto peg of their currencies to the U.S. dollar, they have been able to anchor the inflation expectations of economic agents and maintained monetary policy stability by following the footsteps of the Federal Reserve Bank. Second, all of the central banks in the GCC area have price stability as the ultimate goal of their monetary policy. Finally, during periods of low oil prices, member states in the GCC area financed fiscal deficits through the foreign asset reserves that were accumulated from excess oil revenues. Thus, central banks in the GCC area opted to use foreign asset reserves instead of monetizing the fiscal deficits.

The high degree of convergence and stability among exchange rates in the GCC economies are remarkable when compared to the rest of the world economy (Figure 1.3). There are at least two factors that contribute to the stability of exchange rates in the GCC area. First, the large revenues from oil exports have enabled the GCC economies to accumulate foreign assets reserves that can be used to defend the de facto pegged in case of currency speculations. Another factor is the consistency of economic policies to maintain the de facto pegged, which lends more credibility to the central banks in the GCC area. This reflects the strong support of GCC member states of the de facto peg to the U.S. dollar since the early 1980s until the end of 2002[3]. Since the beginning of 2003, each currency has been de jure pegged to the U.S. dollar as the region moves toward introducing a single currency by 2010.[4]

1.3.2 Fiscal Convergence

By end of 2005, the Ministerial Council defined fiscal convergence in terms of the debt-to-GDP and budget deficit-to-GDP ratios to be 60% and 3%, respectively. Since there are no reliable sources or long observations for the former criteria, I focus only on the later criteria. Figure 1.4 shows the budget balance-to-GDP for the GCC member states from 1970 until 2006. While the degree of comovement is high, the

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[3] With the exception of Kuwait which was pegged to a basket of currencies, where the dollar accounts for the lion share of the basket.

[4] In May 2007, Kuwait opted out of the de jure pegged to its old exchange rate regime (pegged its dinar to a basket of currency).

magnitude of this ratio is different among the GCC economies. The high degree of comovement can be explained by the development in the oil markets. The government budgets in the GCC area are highly dependent on oil revenues. The income from oil exports account for an average of 65% to 90% of the public revenues. Both in early 1970s and since 2002, GCC economies have experienced a large ratio of budget surplus-to-GDP due to the increase of oil prices. However, when oil prices were low from the early 1980s to the late 1990s, GCC governments experienced huge budget deficits because of the difficulty of decreasing the massive government spending on social programs and infrastructure projects enjoyed during the period of high oil prices.

1.3.3 Real Convergence

Real convergence refers to business cycle synchronization among a group of economies. However, there are no well-defined criteria to examine real convergence. Some economic variables such as real GDP growth, labor markets, and trade integration can be examined to analyze the degree of comovement in the GCC area. Figure 1.5 shows how the real GDP growth rates of the GCC member states have comoved with each other for the last two decades with few exceptions. Kuwait had a large negative real GDP growth in 1990 and 1991 due to the Iraqi invasion, while the growth rebounded strongly in the next year due to re-building projects after the war. Similarly, Qatar undertook massive infrastructure projects after discovering natural gas in the mid-1990s. The high degree of comovement of GDP growth rates in the GCC area reflects the importance of the hydrocarbon sector in the GCC economies. This sector on average accounts for almost 35% of the GDP.

The labor markets in the GCC area is highly flexible. While the majority of GCC citizens are employed by the public sector, expatriates provide the labor force needed by the private sector. The flexibility of the labor market comes mainly from the private sector, which can easily accommodate shocks by adjusting the demand for labor. Since all of the GCC economies have had de facto peg to the U.S. dollar, those economies rely on the flexibility of the labor markets instead of exchange rates to absorb economic shocks. The flexibility of the labor market might be diminished if the share of GCC nationals increases over time. This caveat can be overcome through the common market of the GCC area, which went into effect in January 2008, and allows GCC nationals to work anywhere in the GCC area. To take full advantage of the flexibility of the labor market, the Supreme Council of the GCC area might have to allow free mobility of expatriates as well among the GCC economies.

The trade integration in the GCC area has been improving for the last few years. Since the GCC launched the Free Trade Zone in 1983 until the end of 2002, the GCC intra-trade increased from $6 billion to $15.2 billion a year. The GCC economies have started to gain the benefits of the economic integration after enforcing the custom union in January 2003. The GCC intra-trade increased from $15.2 billion in 2002 to over $33 billion by the end of 2005. This represents an average growth rate of 30% a year for the last few years (Figure 1.6).

Since the GCC economies share homogenous economic structures, most of their export and import activity is done with trade partners outside the GCC area. Table 1.2 shows the level of trade integration among the GCC economies. The average GCC intra-trade of exports and imports are 6.3% and 16.9% in 2002, respectively. Four years after establishing the custom union in 2003, the share of intra-trade has not increased; i.e. 5% for exports and 16.8% for imports. Those statistics are low when compared to the European Union before the introduction of the monetary union in 1999 (it was around 50%)[5]. However, those statistics should be interpreted with caution. As long as the GCC economies are heavily dependent on the oil sector, the GCC intra-trade is going to be low as total exports increase with oil exports, and total imports increase as a result of an increase in public spending due to large oil revenues. Therefore, an accurate measure of trade integration can be seen by

[5] Clement van de Coevering (2003)

examining the intra-GCC non-oil trade. Unfortunately, no reliable data are available for intra-GCC non-oil exports or imports.

2 Motivations and Objectives

There are extensive literatures that investigate the feasibility of observing an Optimal Currency Area (OCA). This set of literatures examine empirically some preconditions (i.e. degree of openness, factor mobility, and synchronization of the business cycle) to test the optimality of introducing a single currency. Those preconditions are proposed by Mundell (1961) and McKinnon (1963). This dissertation does not assess the feasibility of observing OCA in the GCC area since the Head of States had already agreed to establish a monetary union by 2010. With the introduction of the monetary union and the single currency, the prospective supernational monetary agency will conduct a single and indivisible monetary and exchange policy. Its policies will be based on the *GCC-wide* economic and financial developments. In this dissertation, I present some empirical tools that can be utilized by the policymakers at the supernational monetary agency to conduct a sound monetary policy.

Since the common monetary policy will be based on the *GCC-wide* economic developments, prospective policymakers at the GCC supernational monetary agency will be scrutinizing a large number of economic variables, both at the national and regional level, in order to obtain a clear signal about the current and future state of the GCC economies. Since economic data is controlled by different agencies, not all economic variables are released simultaneously. In contrast, policymakers will have to make a decision without all of the information available to them yet. To overcome this problem, the objective of the second chapter is to extract a timely single coincident index that can closely track the business cycle evolution of the GCC area by utilizing the Generalized Dynamic Factor Model (GDFM). The constructed indicator may be a good analytical and empirical tool for policymakers at the prospective GCC supernational monetary agency since it provides them with a clear signal about the current economic state by synthesizing high levels of information obtained from different sources.

Constructing a large dataset is a vital first step in order to extract the business cycle information through the GDFM. The business cycle information contained in each variable depends on the utilized dataset since the common factors are defined with respect to economic variables at hand. While there are some well-established and large databases for the U.S. and Euro areas, there is no single dataset containing a large number of macroeconomic variables for the GCC area. I devoted considerable effort to collecting macroeconomic variables from different sources in order to obtain a dataset that covers a wide range of economic phenomena of the GCC economies.

The GDFM presented in chapter 2 is an econometric model that synthesizes information in order to understand the business cycle evolution. However, central banks have recently started to utilize large-scale models based on New Open Economy Macroeconomics (NOEM) approach, where the parameters have structural interpretation. Examples of these models are the Global Economy Model (GEM) by the IMF, BEQM by the Bank of England, BoF by the Bank of Finland, and SIGMA by the Board of Governors of the Federal Reserve Bank of U.S. The NOEM approach can be a valuable tool for policy analysis since NOEM is based on a well-specified microeconomic foundation approach.

The objective of chapter 3 is to layout a Dynamic Stochastic General Equilibrium Model (DSGE) for a small open economy a with fixed exchange rate regime on the GCC area. It is a small open economy model with some nominal and real frictions. The model can be used by the policymakers at the prospective supernational monetary agency to examine the dynamic effects of exogenous shocks on endogenous macroeconomic variables and understand the sources of business cycle fluctuations in the GCC area. Also, the derived model can also serve as a tool for policymakers in assessing alternative scenarios in order to conduct a sound monetary policy at the regional level. Finally, the DSGE model can be used as a "workhorse" to calibrate or estimate the structural parameters of the model when data become available in the future.

Finally, many economic decisions, whether they are made by economists at central banks, fiscal policymakers, businesses, or consumers, are based to some extent on the forecasts of relevant macroeconomic variables such as real output and inflation. Thus, the need for producing accurate forecasts of the key macroeconomic variables has become crucial for both policymakers and economic agents. In a "rich-data environment," where information is scattered over a large number of economic time series, policymakers and applied forecasters have been able to use a variety of data for forecasting any macroeconomic variable of interest. Precisely, the prospective supernational monetary policymakers will be more interested in examining common shocks that drive the GCC economies rather than country-specific shocks. Therefore, from a policy point of view, using a factor model can be a good analytical and empirical tool since estimated common shocks can help to forecast key macroeconomic variables of interest. The objective of chapter 4, then, is to generate short-term forecasts of key macroeconomic variables for the GCC area in a "data-rich environment." The ultimate goal is to measure the efficiency gain from using the dynamic factor model of Forni *et al.* (2005) versus the static factor model of Stock and Watson (2002a, b). Since the previous two models are not comparable, I propose two approaches to make the forecasting equations of those two methods more comparable.

Table 1.1: GCC Economic Indicators

	2004	2005	2006	2007
Nominal GDP ($ billions)	482	608	722	790
Nominal GDP growth	19	26.2	18.7	9.4
Real GDP growth	6.8	7.1	6.7	7
Hydrocarbon GDP	6.2	5.2	3.3	4.5
Non- Hydrocarbon GDP	7.3	8	8	7.9
GDP per capita ($ thousands)	14	17	19.6	20.6
Inflation rate	2.7	4.3	5.2	4.3
Current Account ($ billions)	89.2	167.4	227.3	221.1
% GDP	18.5	27.5	31.4	28

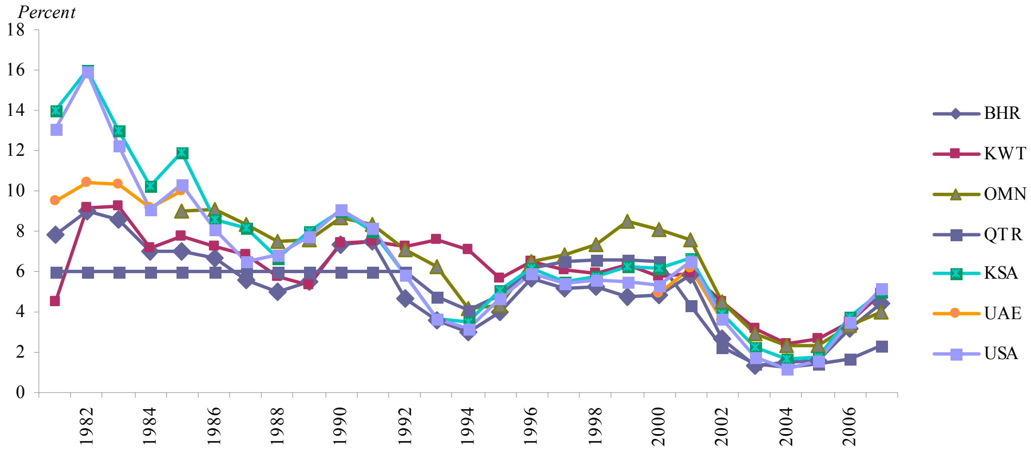
Sources: IFS, WEO, and GCC Secretariat-General

Table 1.2: Destination of GCC Intra-trade

			As % of total exports				
	BHR	KWT	OMN	QTR	KSA	UAE	GCC
2002	5.9	1.7	11.6	6.4	5.4	6.8	6.3
2006	8.3	1.5	7.6	3.6	4.5	4.5	5.0
			As % of total imports				
2002	34.6	11.1	33.2	15.4	2.5	4.8	16.9
2006	43.7	11.6	27.4	10.3	4.3	3.5	16.8

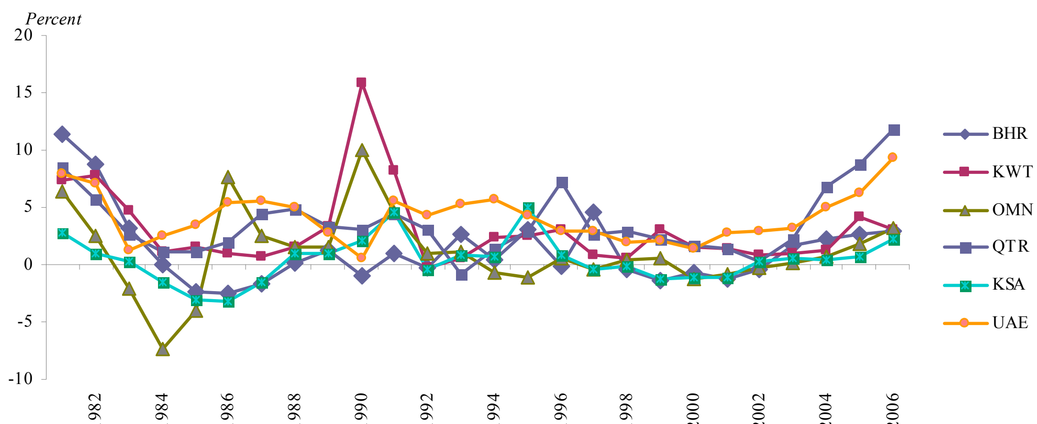
Source: Direction of Trade Statistics (IMF)

Figure 1.1: Interest rates in the GCC economies and U.S.A.



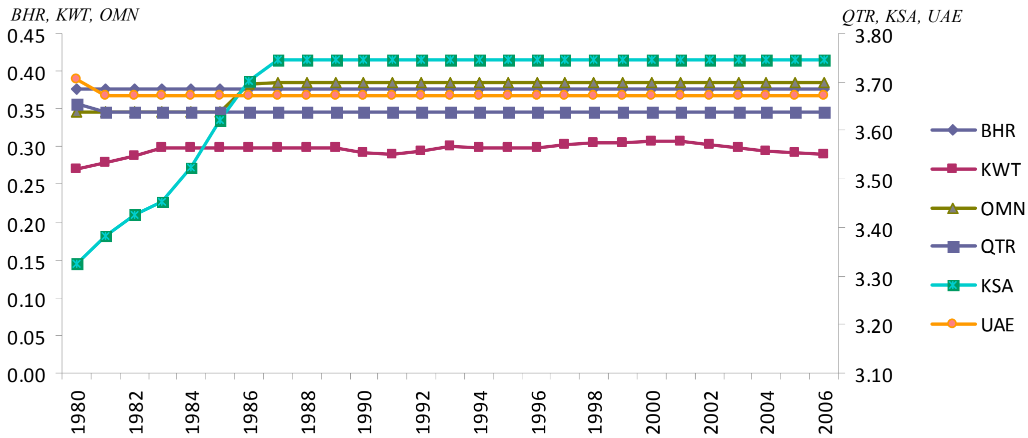
Sources: International Financial Statistics.

Figure 1.2: Inflation in the GCC economies



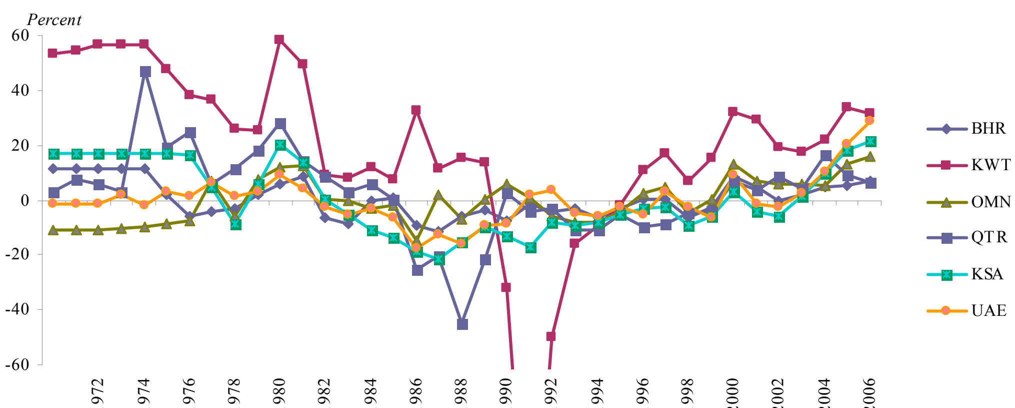
Sources: World Economic Outlook

Figure 1.3: Exchange rates of national currencies per U.S. dollar



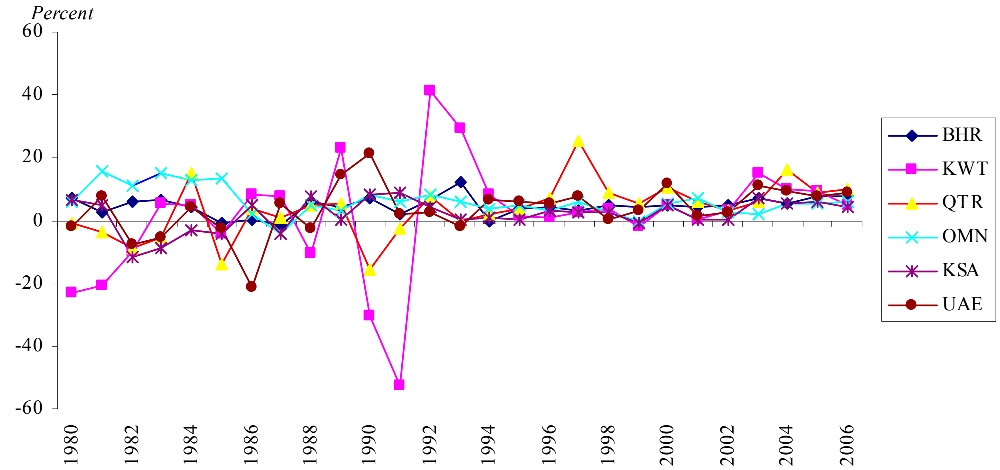
Sources: World Economic Outlook

Figure 1.4: Budget balance-to-GDP



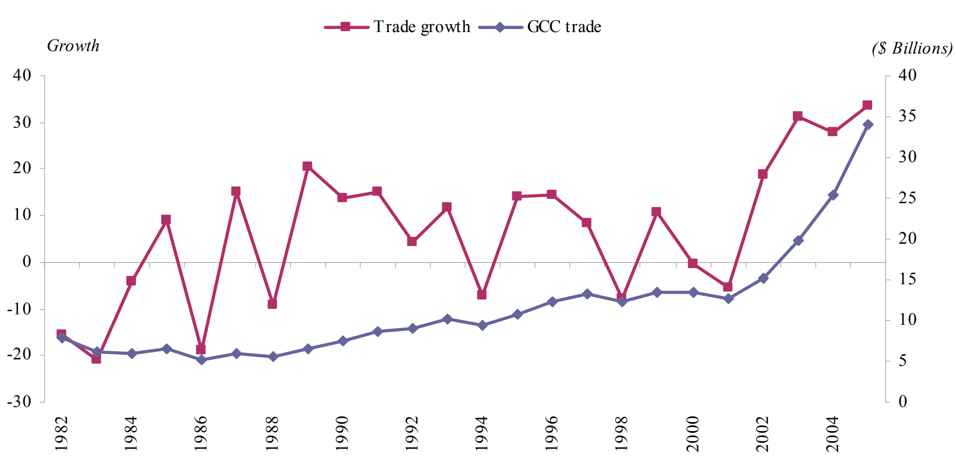
Sources: World Economic Outlook

Figure 1.5: Real GDP growth



Sources: World Economic Outlook

Figure 1.6: GCC total intra-trade (exports plus imports)



Source: Direction of Trade Statistics (IMF)

Chapter 2: A Coincident Indicator of the GCC Area Business Cycle: A Generalized Dynamic Factor Model Approach

2.1 Introduction

The Gulf Cooperation Council (GCC) plans to launch a single currency by 2010 in its six member countries: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates[6]. With the creation of the GCC Monetary Union, a single and indivisible common monetary policy will be based on GCC-wide economic and financial developments. Therefore, prospective policymakers at the GCC supernational monetary agency will be scrutinizing a large number of economic variables, both at the national and regional level, in order to obtain a clear signal about the current and future state of the GCC economies.

In order to assess the business cycle evolution for the GCC area, policymakers will examine any economic variables that may provide them with instant information about the likely economic developments of that region. Since economic data is controlled by different agencies, not all economic variables are released simultaneously. In contrast, policymakers will have to make a decision without all of the information available to them yet. To overcome this problem, I extracted a timely single coincident index that can closely track the business cycle evolution of the GCC area. This indicator may provide policymakers and the business community with a timely and clear signal of the underlying direction of the GCC economies.

The first business cycle indicator was constructed in 1920 by the National Bureau of Economic Research (NBER) to describe the business cycle expansions and contractions for the U.S. economy. The seminal work of Burns and Mitchell (1946)

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[6] In November 2006, Oman indicated that it may not be able to join the monetary union by 2010 because it cannot meet some of the convergence criteria due to its massive infrastructure projects. Furthermore, on May 2007, Kuwait de-pegged its currency to the U.S. dollar. Therefore, these actions may jeopardize the introduction of the single currency by 2010.

describes the business cycle as a type of fluctuation in many time series across different sectors of the economy at the same time:

"A cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own."

Burns and Mitchell (1946) were the first to empirically describe the procedures employed by the NBER to construct a U.S. business cycle indicator. The indicator is constructed by averaging the contemporaneous time series into one single index. In the NBER method, researchers have to determine the peaks and troughs of a "good" reference series and then classify other series as lagging, leading, or coincident variables by how "close" they are to the reference series. Although the NBER methodology is not based on a well-defined statistical model, it still produces an accurate measure of U.S. activity by identifying the troughs and peaks dates that frame U.S. recession and expansion.

As computing power has increased over the last three decades, econometricians have consequently developed more statistically oriented models. One set of these models is the factor model in which a large panel of data is driven by few common shocks. Factor models are merely a formal representation of the index model used by Burns and Mitchell (1946), in which the common factors take on the role of the single index. Therefore, in order to construct a real-time coincident indicator for the GCC area business cycle, this chapter utilizes an innovative approach to factor models. Specifically, it implements the Generalized Dynamic Factor Model (GDFM) proposed by Forni *et al.* (2000, 2004, and 2005).

The constructed indicator may be a good analytical and empirical tool for policymakers at the prospective GCC supernational monetary agency since it provides them with a clear signal about the current economic state by synthesizing high levels of information obtained from different sources. This indicator has three distinct properties: first, it effectively exploits the covariance structure across many economic variables within and among the GCC economies; second, it is purged of high frequency volatility and seasonal components which are irrelevant to business cycle analyses; finally, it is free from both measurement errors and national idiosyncratic shocks.

To achieve the previous desirable properties, Altissimo *et al.* (2001) identify four problems that need to be addressed before constructing any coincident or leading indicator: (i) data is not available on a comparable basis for a long period of time; (ii) data are released in a non-synchronous way; (iii) GDP data is usually not available on a short horizon basis; and (iv) data must be appropriately filtered so that the cyclical component of the GDP growth is continually adjusted as new data become available. Therefore, the first task of this chapter is to construct a GCC area databank covering a wide range of economic variables, which may help in explaining the GCC business cycle fluctuations. Macroeconomic variables are collected from different sources to construct a dataset that covers a wide range of economic phenomena for the GCC economies, because there is not yet a single dataset containing macroeconomic time series for the GCC area. The second task of this chapter is to construct a real time coincident index of the GCC business cycle. This index is similar to the *EuroCoin* index proposed by Altissimo *et al.* (2001) and published monthly by the Centre for Economic Policy Research (CEPR).

The GDFM is a novel development in the theory of factor models. Similar to any factor model, it summarizes the information available in a large cross-section of time series by a few common shocks. That is, the movement of any time series can be represented as the sum of two mutually orthogonal unobservable components: a *common component* and an *idiosyncratic component.* The common component is a linear combination of common shocks, and thereby, it is strongly correlated with the rest of the panel. By contrast, the idiosyncratic component is a variable specific shock and it is weakly correlated across the panel. Since those two components are unobservable, they have to be estimated. The common shocks are estimated by means of dynamic principal components. Unlike the static principal components method, which is based on the eigenvalues decomposition of the contemporaneous covariance matrix, the dynamic principal components method relies on the spectral density matrix of the data wherein data are weighted and shifted across time (dynamic co-variations).

In addition, the real-time coincident indicator (a reference cycle) is defined as the cyclical common component of GDP growth of the GCC area after filtering out measurement errors and idiosyncratic noises, as well as seasonal components. By utilizing GDFM, the business cycle information contained in each variable can be measured as the variance of its cyclical common component relative to its total variance. Further, by using the dynamic principal components instead of static principal components, GDFM allows each variable in the dataset to be classified as pro-cyclical or counter-cyclical with respect to the reference cycle. The GDFM then categorizes the direction of each variable against the reference cycle as lagging, coincident, or leading. All of these results can provide policymakers at the GCC supernational monetary agency with some useful tools to assess the current economic situation in the GCC area and its likely future developments.

The results conveyed in this chapter are distinguishable from the existing literature in the following ways: first, to my knowledge, this is an original effort to generate a real-time coincident indicator for the GCC region by utilizing GDFM; second, while most of the previous literature had been applied to the Euro area, Asian Pacific area, or to the United States, this chapter constructs a business cycle indicator for the GCC area that has been increasingly important in the global economy because of its abundant financial and natural resources. Since the GCC economies are highly dependent on oil revenues, the movement in oil prices may play a vital role in explaining the fluctuations of the business cycle in the GCC area.

In addition, since the GCC supernational monetary agency will base its common monetary policy on GCC-wide economic developments, the constructed real-time coincident indicator can be a useful tool to extract a clear signal of the underlying direction of the GCC area economy. Thus, the constructed indicator may assist monetary policymakers in conducting a sound monetary policy. Finally, while there are some well-established and large databases for the U.S. and Euro areas, there is no single dataset containing macroeconomic time series for the GCC area. The construction of the databank and the real-time coincident indicator in this chapter can facilitate future research on the GCC economies. For future research, the constructed coincident indicator can be compared to the method proposed by Barnett *et al.* (2008), where they use dynamic factor model with regime switching to examine the differences between simple sum monetary aggregates and Divisia Indices over time and over business cycle especially around turning points.

The remainder of this paper is organized as follows: section 2.2 gives an overview of the Generalized Dynamic Factor Model; section 2.3 describes the procedures of constructing the GCC dataset; section 2.4 defines the desired properties and estimation procedures of the coincident indicator of the GCC business cycle; section 2.5 defines the degree of commonality and cyclical behavior of all individual time series in the dataset; section 2.6 examines the proximity of the individual observed economic variables to the latent factors; and section 2.7 concludes.

2.2 Methodology

This section gives an overview of the Generalized Dynamic Factor Model (GDFM) that is proposed by Forni *et al.* (2000, 2004, and 2005). Forni and Lippi (2001) illustrate the representation theory of GDFM. Theoretically, GDFM encompasses an *approximate* factor model of Chamberlain and Rothschild (1983) and Chamberlain (1983), in that idiosyncratic components are allowed to be weakly correlated across the panel, but the factors are static. It also generalizes the factor models of Sargent and Sim (1977) and Geweke (1977), in which the factors are dynamic, but there is no cross-correlation among idiosyncratic components at any lead and lag.

2.2.1 Generalized Dynamic Factor Model

The *i*-th time series, after suitable transformations, is a realization of real-value process from a zero-mean, wide-sense stationary process y_{it}. All y are co-stationary, where stationarity holds for the *n*-dimensional vector process $(y_{1t}, y_{2t}, ..., y_{nt})'$ for any *n*.

Formally, any given time series can be represented as the sum of two mutually orthogonal unobservable components: the common component, χ_{it}, and the idiosyncratic component, ξ_{it} :

$$y_{it} = \chi_{it} + \xi_{it} = b_i(L)\boldsymbol{u}_t + \xi_{it} \tag{1}$$

where y_{it} is a stationary process for the *i*-th time series, *i*= 1,…, *n*, at time *t*, *t* = 1,…, *T*. The common component, y_{it}, is driven by *q* common factors (or common shocks) $\boldsymbol{u}_t = (u_{1t}, u_{2t}, ..., u_{qt})'$, e.g. a technology shock, a demand shock, an oil shock, etc. In any factor models, the number of common shocks *q* is no longer equal to the number of variables *n;* $q << n$.[7] These common shocks are loaded with different coefficients and finite (or infinite) number of lags; that is, variables in the panel are allowed to react heterogeneously to shocks. Thus, the common component can be re-written as a dynamic linear combination of the *q* common shocks:

$$\chi_{it} = \sum_{j=1}^{q} b_{ij}(L) u_{jt} \tag{2}$$

The common component captures the part of the time series which commoves with the rest of macroeconomic variables. By contrast, the idiosyncratic component, ξ_{it}, is

[7] Sargent and Sims (1977), and Giannone *et al.* (2002, and 2004) present some evidence using different datasets that few shocks are capable of explaining the dynamics of macroeconomic data.

driven exclusively by a variable-specific shocks such as measurement errors or variable specific disturbances. The distinction between the common component and the idiosyncratic component has an important implication for policymakers as to how to react to a specific shock. By identifying the source of a shock, they can decide whether to carry out local and sectoral measures, or common measures.

Rewriting the previous equations in a matrix notation:

$$\mathbf{y}_t = \boldsymbol{\chi}_t + \boldsymbol{\xi}_t = B_n(L)\mathbf{u}_t + \boldsymbol{\xi}_t \tag{3}$$

Equation (3) is GDFM[8], where $\mathbf{y}_t = (y_{1t}, y_{2t}, ..., y_{nt})'$, $n \in \mathbb{N}$ and $t \in \mathbb{Z}$, is a stationary process vector with zero mean and finite second order moments $\boldsymbol{\Gamma}_k = \mathrm{E}[\mathbf{y}_t \mathbf{y}'_{t-k}], k \in \mathbb{Z}$, $\boldsymbol{\chi}_t = (\chi_{1t}, \chi_{2t}, ..., \chi_{nt})'$ is the common component vector, and $\boldsymbol{\xi}_t = (\xi_{1t}, \xi_{2t}, ..., \xi_{nt})'$ is the idiosyncratic component vector in which its entries are orthogonal to $u_{j,t-k}$ for any $j, t,$ and k. $\mathbf{B}(L) = B_0 + B_1 L + ... + B_s L^s$ is $(n \text{ x } q)$ polynomial matrix of order s in the lag operator L, whose coefficients represent the impulse response function of y_{it} to any specific shock u_{jt}. Unlike the static factor model, GDFM is dynamic in a sense that the common shocks are allowed to hit the series at different times. Finally, $\boldsymbol{u}_t$ is orthonormal q dimensional white noise vector, i.e. u_{jt} has a unit variance and is orthogonal to u_{st} for any $s \neq j$.

Forni *et al.* (2000) impose two additional assumptions to specify the model by separating the idiosyncratic sources of variation from the common sources of variation. The first assumption allows for a limited serial and cross-sectional correlation among idiosyncratic components, which tends to zero as $i \to \infty$. That is, even though the idiosyncratic sources of variations can be shared by many series, the assumption of boundness guarantees that their effect is limited to a finite number of series. The second assumption ensures a minimum amount of cross-correlation

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[8] References to n will not be made explicit in $\mathbf{y}_t$, $\boldsymbol{\chi}_t$, $\boldsymbol{\xi}_t$, and $\boldsymbol{\Gamma}_k$ to avoid heavy notations. Similarly, explicit reference for T in $\boldsymbol{\Gamma}_k$ will be omitted.

among common components, i.e. the common shocks are present in infinite cross-sectional series.

The moving average representation of GDFM in equation (3) can be easily written in a static form by loading the common factors only contemporaneously. Defining $rx1$ vector as: $\mathbf{f}_t = N(L)\mathbf{u}_t = (\mathbf{u}_t, \mathbf{u}_{t\text{-}1}, ..., \mathbf{u}_{t\text{-}s})'$ where $N(L)$ is an r x q absolutely summable matrix function of *L*. The common component in (3) can be written as:

$$\boldsymbol{\chi}_t = A_n \mathbf{f}_t \tag{4}$$

where $A_n = (a_1', a_2', ..., a_n')' = (B_0^n, B_1^n, ..., B_s^n)$ is n x r matrix, and $r = q(s+1)$ is the number of static factors in $\mathbf{f}_t$. Note that *r* entries of $\mathbf{f}_t$ denote the *static factors*, whereas the *q* entries of $\mathbf{u}_t$ denote the *dynamic factors*. To be precise, u_{1t} and u_{1t-1} are two different static factors of the same common shock. Therefore, the common component is only driven by the *q* exogenous shocks (*dynamic factors*) and it can be expressed at the same time as a linear combination of *r static factors*. In the GDFM model, *q* represents the rank of the spectral density matrix of χ, which is determined by the common sources of exogenous variations to all variables. On the other hand, *r* is the rank of the contemporaneous covariance matrix of χ, which is determined by the degree of heterogeneity of the impulse response functions to the *q* exogenous shocks.

2.2.2 Estimating common components by a one-sided filter

It is not feasible to obtain a consistent estimate and forecast of the common component from equation (3) since the common component estimator is a two-sided filter of $\mathbf{y}_t$ (see Forni *et al.* 2000)[9]. That is, the forecasting performance deteriorates as *t* approaches *T* or 1; which is an unpleasant characteristic for forecasting.

To overcome the previous caveat, Forni *et al.* (2005) propose a two-step method to estimate and forecast the common components using a one-sided filter. In the first step, an estimate of the spectral density matrix $\mathbf{\Sigma}(\theta)$ of the observable $\mathbf{y}_t$ is obtained. Then, the estimated spectral density matrix can be correspondingly decomposed into spectral density matrices of the common and the idiosyncratic components through the *dynamic principal component* method. To close the first step, the Inverse Fourier Transform is applied to the estimated spectral density matrices in order to obtain the covariance matrices of the common and idiosyncratic components at all leads and lags, respectively. The second step consists of estimating the static factors by utilizing the *generalized principal component* approach. Finally, in-sample estimation and forecasting of the common components can be derived by the orthogonal projection of the common components onto the space spanned by the estimated static factors.

Step 1: Estimating the Covariance Structure of the Common and Idiosyncratic Component

The estimated spectral density matrix, $\mathbf{\Sigma}(\theta)$, can be obtained by applying a discrete Fourier Transform to the estimated covariance matrices $\mathbf{y}_t$ of $\mathbf{\Gamma}_k$. The spectral representation theorem allows us to represent the covariance matrices as a sum (integral) of elementary orthogonal periodic processes, which is fruitful for the dynamic analysis. More precisely, for some selected integer $M = M(T)$ [10], the sample covariance matrices $\mathbf{\Gamma}_k = \mathrm{E}[\mathbf{y}_t \mathbf{y}'_{t-k}]$ of $\mathbf{y}_t$ are computed with $k = -M, ..., M$ and $\mathbf{\Gamma}_{-k} = \mathbf{\Gamma}'_k$. The estimated spectral density matrix, $\mathbf{\Sigma}(\theta)$, is then obtained by

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[9] Since the projection coefficients of common components, $b_{ij}(L)$, are obtained by the inverse Fourier transform of the first *q* dynamic eigenvectors, those coefficients are two-sided.

[10] Forni *et al.* (2000) show that a fixed rule $M = M(T) = round(\sqrt{T})$ performs well in simulations.

multiplying the sample covariance matrices by a Bartlett lag-window[11], $\omega_k = 1 - \frac{|k|}{M+1}$, and applying the discrete Fourier Transform:

$$\mathbf{\Sigma}(\theta_h) = \frac{1}{2\pi} \sum_{k=-M}^{M} \omega_k \cdot \mathbf{\Gamma}_k \cdot e^{-i\theta k} \tag{5}$$

The spectra are evaluated at $(2M+1)$ equally spaced frequencies in the interval $[-\pi, \pi]$; i.e. $\theta_h = \frac{2\pi h}{(2M+1)}$ with $h = -M, ..., M$.

The estimated spectral density matrix of the data $\mathbf{\Sigma}(\theta)$ can be decomposed into two orthogonal components as:

$$\underbrace{\mathbf{\Sigma}(\theta)}_{\text{rank } n} = \underbrace{\mathbf{\Sigma}^{\chi}(\theta)}_{\text{rank } q} + \underbrace{\mathbf{\Sigma}^{\xi}(\theta)}_{\text{rank } n} \tag{6}$$

The decomposition in (6) is obtained by applying the dynamic principal component analysis (Brillinger, 1981, chapter 9)[12]. That is, for each frequency of the grid, the eigenvalues and corresponding eigenvectors of $\mathbf{\Sigma}(\theta_h)$ are computed. Then, by ordering the eigenvalues in descending order and collecting the corresponding eigenvectors for each frequency, we obtain the *j*-th dynamic eigenvalue functions $\lambda_j(\theta)$ of $\mathbf{\Sigma}(\theta)$ and the corresponding dynamic eigenvectors functions $\mathbf{p}_j(\theta) = (p_{j1}(\theta) .... p_{jn}(\theta))$, for $j = 1, ..., n$. For each frequency, denote $\mathbf{\Lambda}_q(\theta)$ to be a q x q diagonal matrix, $\text{diag}(\lambda_1(\theta), ..., \lambda_q(\theta))$, of the spectral eigenvalues, and the corresponding n x q eigenvectors by $\mathbf{P}_q(\theta) = (\mathbf{p}_1(\theta), ..., \mathbf{p}_q(\theta))$. Following Forni *et al.* (2000), the estimated spectral density matrix of the common component $\boldsymbol{\chi}_t = (\chi_{1t}, ..., \chi_{nt})'$ is given by:

[11] Bartlett weights are needed to avoid biases caused by truncating the population spectral density.

[12] Static principal component analysis does not take into account the autocovariances, but just the covariances. Therefore, it does not maximize the variance explained. Also, Brillinger (1981) shows that the first q principal components are the best linear combinations of the data.

$$\mathbf{\Sigma}^{\chi}(\theta)=\mathbf{P}_q(\theta)\mathbf{\Lambda}_q(\theta)\mathbf{P}_q(\theta)' \tag{7}$$

It follows immediately from (7) that the estimated spectral density matrix of the idiosyncratic components is then computed as the difference:

$$\mathbf{\Sigma}^{\xi}(\theta)=\mathbf{\Sigma}(\theta)-\mathbf{\Sigma}^{\chi}(\theta) \tag{8}$$

Finally, applying the Inverse Discrete Fourier Transform to (7) and (8) gives the estimated covariance matrices of the common components at different leads and lags:

$$\begin{aligned}\mathbf{\Gamma}_k^{\chi}&=\left(\frac{2\pi}{2M+1}\right)\sum_{h=-M}^{M}\mathbf{\Sigma}^{\chi}(\theta_h)\cdot e^{i\theta_h k}\\ \mathbf{\Gamma}_k^{\xi}&=\left(\frac{2\pi}{2M+1}\right)\sum_{h=-M}^{M}\mathbf{\Sigma}^{\xi}(\theta_h)\cdot e^{i\theta_h k}\end{aligned} \tag{9}$$

Until now, we have not imposed any criteria on how to choose the optimal number of common shocks, q. Forni *et al.* (2000) propose a decision rule to determine q. To choose the optimal number of q, the eigenvalues of the dataset's spectral density matrix, $\mathbf{\Sigma}_k(\theta_h)$ for $k=1,....,n$, have to satisfy the following two conditions:

1. The average over the frequencies θ of the first q eigenvalues diverges, whereas the average of the $(q+1)^{\text{th}}$ eigenvalues is relatively stable.
2. When $k=n$, there is a substantial difference between the explained variance of the first q^{th} principal components, and the variance explained by the $(q+1)^{\text{th}}$ principal components.

With regard to the first criteria, figure 2.1 shows the first 20 dynamic eigenvalues averaged over low frequencies, i.e. business cycle frequencies defined to be more than 5 quarters. It is plotted against the number of the cross-sectional units n. The figure clearly shows that only the first 3 dynamic eigenvalues diverge most probably, whereas the remaining eigenvalues are bounded.

The second criteria suggests to add a factor at a time until the additional variance explained by the last dynamic principal component is at least larger than a pre-specified critical value, i.e. 5% or 10% of the total variance. As in Altissimo *et al.*

(2001) and Forni *et al.* (2000), I set the marginal explained variance at 10%. Figure 2.2 shows the percentage of variance explained by the first 10 dynamic principal components. Each of the first 3 dynamic principal components explains more than 10%. As it can be seen, the first 3 dynamic principal components together explain on average 50% of the total variance of the 82 series. Therefore, the number of the common shocks that is chosen throughout the remainder of this chapter is in accordance with the previous empirical literatures. For instance, Forni and Reichlin (1998) and Forni *et al.* (2000) find $q = 2$, Reijer (2005) and Schneider and Spitzer (2004) find $q = 3$, and Altissimo *et al.* (2001) find $q = 4$.

The estimates of the covariance matrices of the cyclical components, $\boldsymbol{\chi}_t^C = (\chi_{1t}^C, \chi_{2t}^C, ..., \chi_{nt}^C)'$,[13] can be obtained by applying the Inverse Discrete Fourier Transform to the frequency band of interest $[-2\pi/\tau, 2\pi/\tau]$:

$$\mathbf{\Gamma}_k^{\chi^C} = \left(\frac{2\pi}{2H+1}\right) \sum_{h=-H}^{H} \mathbf{\Sigma}^{\chi}(\theta_h) \cdot e^{i\theta_h k} \tag{10}$$

where H is defined by the condition $H/(2M+1) > \tau$ and $(H+1)/(2M+1) < \tau$. Thus, to eliminate waves of periodicity shorter than 5 quarters, I set $\tau = 5$.

Step 2: Estimating and Forecasting the Common Components

Forni *et al.* (2005) estimate the *r* contemporaneous linear combination of $\mathbf{y}_t$ as the solution of the *generalized principal component* problem. The information criteria proposed by Bai and Ng (2002) will be used to determine *r*. More precisely, starting from the estimated covariance matrices, (10), Forni *et al.* (2005) compute the

[13] Like any stationary variable, the common component of variable *i* can be decomposed into the sum of waves of different periodicity, i.e. $\chi_{it} = \chi_{it}^C + \chi_{it}^{NC}$, where χ_{it}^C is represented by smooth waves with long and medium-run periodicity, while χ_{it}^{NC} is represented by high-frequency volatility.

generalized eigenvalues μ_j; i.e. n complex number solving $det(\mathbf{\Gamma}_0^{\chi} - \mu\mathbf{\Gamma}_0^{\zeta})$, and the corresponding eigenvectors $\mathbf{Z}_j$ for $j = 1,....,n$. The vectors are the solution of:

$$\mathbf{Z}_j\mathbf{\Gamma}_0^{\chi} = \mu_j\mathbf{Z}_j\mathbf{\Gamma}_0^{\zeta} \tag{11}$$

and the normalizing condition:

$$\mathbf{Z}_j\mathbf{\Gamma}_0^{\zeta}\mathbf{Z}_i' = \begin{matrix} 0 \text{ for } j \neq i \\ 1 \text{ for } j = i \end{matrix} \tag{12}$$

By ordering the eigenvalues in descending order and taking the corresponding eigenvectors of the r largest eigenvalues, the estimated static factors are the *generalized principal components*:

$$v_{jt} = \mathbf{Z}_j\mathbf{y}_t,\ j = 1,....,r \tag{13}$$

Rewriting (13) in a matrix notation:

$$\mathbf{v}_t = \mathbf{Z}\mathbf{y}_t \tag{14}$$

The generalized principal components deliver the “efficient” r contemporaneous linear combinations of $\mathbf{y}_t$, which have the smallest idiosyncratic-common variance ratio. That is, a variable with a lower idiosyncratic variance gets a higher weight. Having obtained the r generalized principal components, the optimal h-step ahead forecast of the common component based on the available information at time t is given by:

$$\begin{aligned} \boldsymbol{\chi}_{T+h\ |T} &= [\mathbf{\Gamma}_h^{\chi}\mathbf{Z}(\mathbf{Z}\mathbf{\Gamma}_\mathbf{0}\mathbf{Z}')^{-1}][\mathbf{v}_T] \\ \boldsymbol{\chi}_{T+h\ |T} &= [\mathbf{\Gamma}_h^{\chi}\mathbf{Z}(\mathbf{Z}\mathbf{\Gamma}_\mathbf{0}\mathbf{Z}')^{-1}][\mathbf{Z}\mathbf{y}_T] \end{aligned} \tag{15}$$

Equation (15) gives the one-sided estimators of the common components, which avoid the end-of-sample inconsistency problems. Forni *et al.*(2005) show the consistency of (15) as $(n,T) \to \infty$, i.e. $\boldsymbol{\chi}_{t+h}$ converges to the space spanned by the present and the past of $u_{1t}, u_{2t}, ..., u_{qt}$.

2.3 Building a GCC Area Database

Constructing a large dataset is a vital first step in order to extract the business cycle information through the GDFM. The business cycle information contained in each variable depends on the utilized dataset since the common factors are defined with respect to economic variables at hand. While there are some well-established and large databases for the U.S. and Euro areas, there is no single dataset containing a large number of macroeconomic variables for the GCC area. I devoted considerable effort to collecting macroeconomic variables from different sources in order to obtain a dataset that covers a wide range of economic phenomena of the GCC economies. The final database, which is quantitatively and temporally rich, is utilized to construct the coincident indicator that can precisely describe the underlying direction of the GCC business cycle.

By including a large number of economic variables, the idiosyncratic source of variation can be minimized simply by the process of aggregation. Since more data usually improve the statistical efficiency of estimators, this is only true for surveys where the random sample is chosen to be representative of the population. However, Boivin and Ng (2006) use simulation and empirical example to prove that increasing the size of the dataset beyond a certain point is not desirable. They show that factors extracted from a smaller pre-screened dataset are better than the ones extracted from a larger dataset. Therefore, the quality of the dataset is more important than the size of the dataset.

In order to construct the GCC database, I applied the same two criteria used by Altissimo *et al.* (2001) to select which variables to include in the final dataset. The first requirement is the length of the time series. The longer the time series, the more information it contains about its cyclical behavior. The other requirement is homogeneity of variables over time and across countries in order to avoid overweighting any single country in the GCC database. I collected data from different data sources such as International Financial Statistics (IFS), World Economic

Outlook (WEO), Direction of Trade Statistics (DOTS), Organization for Economic Cooperation and Development (OECD), Federal Reserve Economic Data (FRED), US Department of Energy (Energy Information Administration), and the GCC Secretariat General. The final dataset consists of 82 time series with quarterly data from 1980Q1 to 2007Q2. It covers the major different sectors of the GCC economies. It also includes some international variables that might be relevant to explain the business cycle evolution of the GCC area. Table 2.1 presents a detailed list of all time series contained in the final dataset.

The economic variables contained in the final dataset are regrouped into seven homogenous groups:

- Financial variables: interest rates and exchange rates
- Price variables: consumer prices and commodity prices (real oil prices)
- Monetary variables: foreign assets and monetary aggregates
- International liquidity: total foreign reserves
- National accounts: real GDP[14]
- Foreign trade: exports and imports
- Industrial production: crude petroleum production

The final dataset underwent the following three steps in order to prepare the final dataset for the estimation stage:

1. Each time series is seasonally adjusted using the *Tramo* (Time Series Regression with ARIMA noise, Missing observation, and Outlier) and *Seats* (Signal Extraction in ARIMA Time Series) procedures proposed by Gomez and Maravall (1999). Running simultaneously, the *Tramo* procedure first

[14] The quarterly data of the aggregate GCC GDP is the linear interpolation of the yearly data. As a result, the quarterly GDP data is a proxy of the unobserved GDP figures. The measurement error contained in this approximation procedure is most unlikely to be correlated with the dynamic common shocks because this measurement error only affects the GCC GDP variable. Therefore, it purged out during the estimation process of the common shocks.

estimate a regression model with possible ARIMA errors, interpolate missing values, and detect all types of outliers (i.e. additive outliers, transitory changes, and level shifts) Then the *Seats* procedure utilizes the ARIMA model to decompose each time series into unobserved components (i.e. trend cycle, seasonal, and irregular). Therefore, the outcome of the *Tramo/Seats* procedure is a time series that is free of outliers and seasonally adjusted.

2. Both the estimation of the spectral density matrix and the GDFM require each time series to be covariance stationary. To induce stationarity, the first difference of natural logarithms was taken for *Tramo/Seats* adjusted time series, with the exception of interest rates and time series with negative values where a simple first difference was taken.
3. Finally, each time series was normalized so that it has a zero sample mean and a unit variance. This procedure delivers a series that is independent of any unit of measurement. This normalization is a necessary step in order to avoid overweighting any given time series with a large variance during the estimation of the spectral density matrix. Thus, the spectral estimation is conducted on the normalized observations:

$$y_{it} = \frac{(y_{it} - \overline{y}_i)}{s_i}, \text{ where } \overline{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it} \text{ and } s_i = \frac{1}{T-1}\sum_{t=1}^{T}(y_{it} - \overline{y}_i)^2$$

2.4 A Coincident Indicator for the GCC Business Cycle

2.4.1 Definition of the Coincident Indicator Properties

The proposed coincident indicator for the GCC business cycle is the common component of the GCC GDP growth at business cycle frequencies[15]. The reason for choosing the cyclical common component of the GDP instead of any other measure is

[15] The GDP in the GCC area is the weighted average of the GDP of the six economies in the GCC region $(\sum \omega_i \cdot GDP_{i,t})$, where weights are calculated based on PPP valuation of each country GDP.

that the GDP is usually considered the broadest measure of economic activity. By defining the coincident indicator as the common component of GDP growth at cyclical fluctuations, it coincides with a “growth cycle” or a “deviation cycles” definition. That is, it is the deviation of the GDP growth from its long-run trend (zero growth in the long-run). Therefore, a positive value of the coincident index signals a period of growth above the long-run growth rate, and vice versa. The “growth cycle” definition is different from the “cyclical cycle” definition employed in the NBER methodology, which looks at the absolute values of economic activity.

In addition, the importance of taking the GDP growth at business cycle frequencies stems from the fact that economic variables comove with each other at business cycle horizons. To empirically examine the importance of business cycle comovement, figure 2.3 and figure 2.4 show the spectral density functions and the average spectral shape of all time series in the dataset across all frequencies. Both figures explain how the overall variance is distributed across different periodicities. If business cycle frequency is defined to be more than five quarters (i.e. frequencies less than 1.25), then it is clear that fluctuations at business cycle frequencies account for a large portion of the variance.

2.4.2 Properties of the Coincident Indicator

The proposed indicator must meet the following three criteria to be economically meaningful indicator in explaining the GCC area business cycle[16]:

(i) cross-sectional smoothing

The idiosyncratic component of each variable captures both the variable-specific shocks (i.e. shocks to specific industry), and local-specific shocks (i.e. shocks affect only a specific region). These two kinds of shocks should not explain a large fraction of the GCC GDP growth since the aggregation process minimizes the idiosyncratic component. These shocks should be monitored by sectoral and local

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[16] See Cicconi (2005) and Altissimo *et al.* (2001)

policy makers. On the other hand, policymakers at the GCC supernational monetary agency should focus on monitoring only the common shocks, which affect the GCC-wide economic developments. Furthermore, the idiosyncratic component also captures measurement errors, because the GDP data are obtained by estimation procedures, not by direct observation, and they are also aggregated from heterogeneous sources. These errors are cross-sectional weakly correlated. Therefore, the coincident indicator of GCC business cycle should be free from all sources of idiosyncratic variations.

(ii) intertemporal smoothing

Since the common component of any variable is stationary, then it can be decomposed into the sum of waves of different periodicity. That is, the common component can be represented as the sum of a cyclical component, χ_{it}^{C} , represented by smooth waves with long and medium-run periodicity, and a non-cyclical component, χ_{it}^{NC} , represented by waves with short-run periodicity such as seasonal and high-frequencies volatility. The coincident index should be washed out from a non-cyclical component.

(iii) updating

In order for the proposed indicator to be a useful tool, it has to provide policymakers with timely information about the GCC-wide economic developments. At every time *t,* common factors have to be estimated in order to construct the common components. However, since not all data will be available at time *t* or even for $t-1$, then some variable have to be forecasted. Therefore, the coincident indicator will be subject to small revision after short period as new data release. Clearly there is a prediction error contained in the estimated indicator; however, the GDFM can reduce it by exploiting the information coming from the cross-section variables (especially the leading variables). Moreover, by classifying variables into leading, coincident, or lagging with respect to the reference cycle, we can use the leading variables to explain the likely development of the coincident indicator.

2.4.3 The Construction of a Coincident Indicator

The estimation procedures of the coincident indicator consist of three steps. The first step consists of estimating the covariance matrices of the common and idiosyncratic components. The second step consists of estimating the static factors. These steps are the two-step estimation procedures of Forni *et al.* (2005), which are described in section 2.2.2. The final step consists of estimating the cyclical component of the GCC GDP growth, χ_{1t}^{C} , by projecting χ_{1t}^{C} onto the leads and lags of the static factors (i.e. projecting χ_{1t}^{C} onto $\mathbf{v}_{t-m},...,\mathbf{v}_{t},...,\mathbf{v}_{t+m}$). The projection coefficients derived by the covariance matrices of the cyclical components and not from the OLS estimation. Formally, set $\mathbf{V_t = (v}_{t-m},...,\mathbf{v}_{t},...,\mathbf{v}_{t+m})$,

$$\mathbf{W}=\begin{pmatrix} \mathbf{Z} & \mathbf{0}_{n\,\mathrm{x}\,r} & \cdots & \mathbf{0}_{n\,\mathrm{x}\,r} \\ \mathbf{0}_{n\,\mathrm{x}\,r} & \mathbf{Z} & \cdots & \mathbf{0}_{n\,\mathrm{x}\,r} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0}_{n\,\mathrm{x}\,r} & \mathbf{0}_{n\,\mathrm{x}\,r} & \cdots & \mathbf{Z} \end{pmatrix}$$

and $\mathbf{Y}_t = (\mathbf{y}'_{t+m}...\mathbf{y}'_{t}...\mathbf{y}'_{t-m})'$, then $\mathbf{V}_t = \mathbf{W}\mathbf{Y}_t$. The sample covariance matrix of $\mathbf{Y}_t$ can be represented as:

$$\mathbf{M}=\begin{pmatrix} \mathbf{\Gamma}(0) & \mathbf{\Gamma}(1) & \cdots & \mathbf{\Gamma}(2m) \\ \mathbf{\Gamma}'(1) & \mathbf{\Gamma}(0) & \cdots & \mathbf{\Gamma}(2m-1) \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{\Gamma}'(2m) & \mathbf{\Gamma}'(2m-1) & \cdots & \mathbf{\Gamma}(0) \end{pmatrix}$$

and $E(\boldsymbol{\chi}_t^C \mathbf{Y}'_t) = \mathbf{R}$, where

$$\mathbf{R} = (\mathbf{\Gamma}'_{\chi^C}(m) \;...\; \mathbf{\Gamma}'_{\chi^C}(0) \;...\; \mathbf{\Gamma}'_{\chi^C}(m))$$

Finally, to estimate the cyclical components, we project $\boldsymbol{\chi}_t^C$ on $\mathbf{V}_t$:

$$\boldsymbol{\chi}_t^C = \mathbf{RW}(\mathbf{W}'\mathbf{MW})^{-1}\mathbf{W}'\mathbf{Y}_t \qquad (16)$$

There is one problem with the estimates of (16), that is, $\mathbf{y}_{t+h}$ is not available for $h > 0$. To solve the mentioned problem, we substitute the forecast of the common components, $\boldsymbol{\chi}_{T+h}$, from (15) in place of $\mathbf{y}_{t+h}$, and then apply equation (16).[17]

Figure 2.5 shows the coincident indicator for the GCC area estimated with quarterly data over the period 1981.Q1 to 2007.Q2. Because the indicator coincides with a "growth cycle" definition, a positive value of the coincident index signals a period of growth above the long-run growth rate (zero growth in the long-run), and vice versa. The indicator can be naturally interpreted as the quarterly growth rate of the GDP in the GCC area. Figure 2.5 also compares the extracted coincident indicator to the actual quarterly growth rate of GDP in the GCC area. With the exception of the early 1980s and during the second Gulf war (1990-1991), the figure clearly shows how the coincident indicator closely tracks the movements of the GDP growth for the GCC area. Indeed, their correlation over the whole sample is around 87 percent.

To compare the coincident indicator with respect to countries in the GCC area, figure 2.6 reports the behavior of each country-common component against the coincident indicator. It should be noted that the former should not be interpreted as national indicators since they do not contain a nation specific component. It can be interpreted as the part of the national cycle that is common across all of the GCC economies. With the exception of Bahrain and Oman, there is close comovement between the common component of the GDP growth for each country and the GCC area coincident indicator. This is not surprising since both Bahrain and Oman are the two most diversified economies (less dependent on oil income) in the GCC area, and their weights in the GCC GDP are the smallest. Moreover, both Bahrain and Oman have been using their limited oil revenues to diversify their economic structures and develop the private sector. For example, Bahrain is trying to support the private sector by developing a high-tech service industry, whereas Oman is trying to support both

[17] For more details on the treatment of the end-of-sample unbalance, see Altissimo *et al.(*2001)

the gas and tourism industries. In contrast, the common components of GDP growth in Qatar and UAE have over-performed the GCC area at the end of the sample. This is due to the fact that both of these countries have been enjoying a high record of public and private investments, especially in the financial sector, tourism infrastructures, and real-estate sector.

2.5 Degree of Commonality and Cyclical Behavior of the Variables

As it is shown in section 2.2.1, each time series can be decomposed into two components: the common component and the idiosyncratic component. Formally, we can measure the business cycle information contained in each variable by:

$$C_i = \frac{var(\chi_i^{NC})}{var(y_i)} \tag{17}$$

where C_i represents the degree of commonality of variable *i*. Table 2.1 shows the degree of commonality for each variable in the dataset. Averaging over cross-sectional units, the cyclical common components explain almost 40% of the series' total variance. This result is in line with Cristadoro *et al.* (2005) and Altissimo *et al.* (2001). The degree of commonality of economic variables ranges between 65% and 11%. For the key variable of interest, the commonality ratio of the GCC GDP growth is 57%. Also, by examining the degree of commonality of all variables in the dataset, it is easy to see that nominal effective exchange rates, oil prices, consumer prices, oil productions, imports, exports, net foreign assets, and monetary aggregates have greater commonality ratios compared to interest rates and yield spreads.

As a by-product of utilizing the GDFM, we can categorize the cyclical behavior of each macroeconomic variable with respect to the reference cycle as pro-cyclical or counter-cyclical. We can then re-categorize each variable as a lagging, coincident, or leading variable against the reference cycle. It is important to first determine the relevant reference cycle. As it was mentioned in section 2.4.1, the GDP figures are viewed as a broad measure of the aggregate economic activity. Thus, in this chapter, the reference cycle is defined as the common component of the GCC GDP growth at the cyclical business cycle periodicities.

To determine the direction and timing of each time series, I first computed the cross-spectral density of each common component with respect to the reference cycle, $\sigma_{i,GDP}(\theta)$. Then, to classify each time series as pro-cyclical or counter-cyclical, I computed the phase angle shifts of each variable with respect to the reference cycle at the zero frequency, $\phi_{i,GDP}(0)$. A variable is classified as pro-cyclical if $\phi_{i,GDP}(0) = 0$ (positive long-term correlation), and as counter-cyclical if $\phi_{i,GDP}(0) = \pi$ (negative long-term correlation). Grouping time series by sector, table 2.2 shows the majority of the series in the dataset (60%) are classified as pro-cyclical variables with respect to the reference cycle, whereas the remaining are classified as counter-cyclical.[18]

Having split the variables into either pro-cyclical or counter-cyclical variables, I can further split these two groups as lagging, coincident, or leading variables by calculating the time lag at the business frequency, $\psi_{i,GDP}(\theta) = \frac{\phi_{i,GDP}(\theta)}{\theta}$. The time lag is calculated at a frequency $\theta = \frac{2\pi}{5}$, where I assume an average length of the business cycle to be more than five quarters. A variable is classified as lagging when the time lag is lower than -1 (quarter), leading when it is more than 1, and coincident otherwise. Out of 82 series, table 2.2 shows 18% lagging, 55% to be coincident, and 27% to leading.

2.5.1 Business cycle: stylized facts

In this section, I analyze by sector the cyclical behavior of economic variables with respect to the reference cycle. Detailed results are provided in table 1.1.

Production

[18] Table (1) contains the results for each variable in the dataset.

The *industrial production* indices (petroleum production index and oil production level) exhibit strong comovement within the cross-section time series, where almost 40% of their variation can be explained by the first three common dynamic factors. Since the level of industrial production is a narrower measure of the overall aggregate economic activity, the direction and timing of industrial production tend to coincide with the reference cycle. Further, all industrial production indices are pro-cyclical and coincident; that is, they tend to rise when GDP growth rises, and fall when GDP growth declines.

The *Gross Domestic Product* for each of the economies in the GCC area, with the exception of Oman, exhibits a pro-cyclical and coincident behavior with respect to the reference cycle. The average explained variance by the first three common factors at cyclical frequencies is almost 50%.

The direction and timing of the *Foreign Gross Domestic Product* does not reveal a systemic behavior with respect to the reference cycle. While Euro area GDP is pro-cyclical and leading, the U.S. and Japan GDP are counter-cyclical and coincident. That is, the movement in the Euro area economies gives some signals as to how the GCC business cycle is likely to develop.

The previous result is supported by the fact that the Euro area is a closer trade partner than the U.S. By examining the Direction of Trade Statistic (DOTS) for the GCC area, it can be noticed that exports of the GCC area to the Euro area is almost twice as much as compared to the U.S. for most of the sample from 1980 to 2006. Another possible explanation of the counter-cyclical behavior between the GCC area and the U.S. GDP is through the adopted fixed exchange rate regimes in the GCC region. To explain the exchange rate channel, assume that the U.S. economy is going through a slowdown. The Federal Reserve Bank will ease the monetary policy by lowering the interest rate in order to stimulate the U.S. economy. As a result, the GCC central banks will lower their interest rates in order to maintain the fixed exchange rate regimes. While the slowdown in the U.S. economy will have a negative effect on the GCC GDP by reducing the demand for oil, the reduction in interest rates will have a positive effect by stimulating the GCC economies. It is most likely that the effect of interest rates will offset the lower demand by the U.S. since the interest rates pass-through channel is faster than the change in the elasticity of oil demand.

Financial Variables

The *interest rates* (deposit rate and lending rate) for the GCC area are pro-cyclical and coincident with respect to the reference cycle. Due the fixed exchange rate regimes in the GCC area, the nominal interest rates coincide also with the movement in the U.S. Treasury bill rate, as implied by the Uncovered Interest Parity (UIP).

The *yield spread*, which is defined as long-term (corporate bond) interest rate minus short-term (government bond) interest, is usually positive and slopes upward to reflect the liquidity premium. If it starts to flatten or invert, it is most likely to signal an increasing possibility of coming recessions as the monetary policy starts to tighten. Hamilton and Kim (2002) show evidence of how the yield curves flatten or invert prior to all eight U.S. recessions between 1953 and 1998. Therefore, yield spreads are a good predictive signal of the future aggregate activity. The U.S. government yield spread and corporate yield spread appear to be counter-cyclical and leading with respect to the GCC reference cycle. This result confirms our previous result of the opposite movement between the GCC reference cycle and the U.S. GDP.

The *nominal effective exchange rates* display a clear-cut picture of their cyclical behaviors. They are counter-cyclical and leading by two quarters. Similar to the yield spreads, the movements of the exchange rates provide good signals about the underlying direction of the reference cycle.

In conclusion, the leading property of most of the financial variables is in accordance with the economic literature, where financial asset prices reflect market expectations about future economic outcomes.

Prices

The average explained variance by the first three common factors of *GCC consumer prices* is around 40%. More than 67% of consumer prices are pro-cyclical. The timing of consumer prices with respect to the reference cycle is mixed. While 50% of consumer prices appear to be lagging, the remaining coincide with the reference cycle. The existence of some lagging consumer prices is not surprising if we assume that some nominal frictions, such as price stickiness, exist.

With regard to the *oil prices*, it is not surprising to find a clear picture of its cyclical behavior. Since the GCC area is heavily dependent on the oil revenues, the movement of oil prices is pro-cyclical and coincident with the reference cycle.

The *foreign consumer prices* in the Euro area, Japan, and U.S. appear to be counter-cyclical and leading with respect to the reference cycle. As the foreign consumer prices start to rise, the currencies of the GCC economies depreciate in real term, which causes exports to increase. As a result, the GCC GDP starts to increase due to the positive effect of the net exports. The leading time of foreign consumer prices vary from one quarter and a half to two quarters and a half.

Monetary Aggregates

In macroeconomic literatures, the cyclical behavior of *money supply* with respect to the aggregate economic activity is controversial. In the seminal work of Friedman and Schwartz (1963), they analyzed the money supply behavior for over a century. They concluded that money supply tended to be pro-cyclical and leading. Since the GCC economies have fixed exchange regimes against the U.S. dollar, money supply is determined exogenously by the U.S. Federal Reserve Bank (i.e. monetary policy in the GCC area is passive). The money supply measure used in this chapter is M2. It exhibits a counter-cyclical and leading behavior with the reference cycle. If the money supply is pro-cyclical and leading in the U.S., then the counter-cyclical behavior of the money supply in the GCC area is consistent with our previous findings that the U.S. GDP is counter-cyclical to the GCC reference cycle.

The *net claim on central governments*, defined as claim on central government by banks minus central government deposit at the central bank, shows consistent cyclical behavior pattern with respect to the reference cycle. In most cases, they are counter-cyclical and leading (Bahrain and United Arab Emirates are lagging). This result is not surprising since all of the oil companies in the GCC area are owned by the central governments. Thus, as oil revenues accumulate over time, the central governments start to decrease their debt positions with the private banks.

The *total international reserves*, defined as foreign exchange plus SDR and the reserve position at the International Monetary Fund, appear to be pro-cyclical and coincident with respect to the reference cycle. Only Bahrain and Kuwait show counter-cyclical behavior. The pro-cyclical behavior of the international reserve is explained by the fact that oil revenues come in the form of the U.S. dollars, since oil is quoted in the commodity markets in U.S. dollars.

International Trade

The cyclical behavior of exports and imports show a clear-cut pattern. While exports are pro-cyclical and coincident, imports are pro-cyclical and lagging. Since the GCC economies are oil-based economies, then as oil exports rise, so does the GDP. As a result of increasing GDP, governments and private sectors increase their spending, which causes imports to rise. While the export sector coincides with the reference cycle, the import sector lags the reference cycle as both governments and private spending take some time to reflect the rise in the GDP.

2.6 Observed Economic Variables and Latent Factors

In many economic theories, it has been found that a small set of common factors explain a large part of variation in cross-section variables. For instance, the Capital Asset Pricing Theory (CAPM) assumes that the variation in all assets returns can be explained by a one systemic common factor, which is the market return. Similarly, the Arbitrage Pricing Theory (APT) is a generalized version of CAPM. It assumes that a small set of common factors can explain most of the variation in all assets returns. The previous two examples do not give an explicit definition of the number of common factors. Also, they do not specify the observed counterpart variables of these common factors in order to conduct empirical testing of these theories.

With the advancement of modeling and estimating factor models, many of the empirical applications have tried to replace the theoretical unobserved common factors with the statically extracted factors. For example, in this chapter, the unobserved common factors in the common component are replaced by the estimated statistical dynamic common factors from the GDFM. The drawback of this procedure is that the estimated statistical common factors do not have any economic interpretation. To overcome this problem, Bai and Ng (2006) propose a test to compare if the individual observed variables and the latent factors are approximately the same. The proposed two statistics are:

$$NS(j) = \frac{\widehat{\operatorname{var}}\left(\hat{\boldsymbol{\varepsilon}}(j)\right)}{\widehat{\operatorname{var}}\left(\hat{\mathbf{y}}(j)\right)} \tag{18}$$

$$R^2(j) = \frac{\widehat{\operatorname{var}}\left(\hat{\mathbf{y}}(j)\right)}{\widehat{\operatorname{var}}\left(\mathbf{y}(j)\right)} \tag{19}$$

where $\hat{\boldsymbol{\varepsilon}}(j)$ is the measurement error obtained after subtracting the individual observed variables $\mathbf{y}(j)$ from the estimated observed variables $\hat{\mathbf{y}}(j)$. The latter is obtained by regressing the individual observed variables on the latent factors, i.e. $\hat{y}_{jt} = \hat{\beta}_j \mathbf{F}_t$, where $\hat{\beta}_j$ is obtained by the least squares method, and $\mathbf{F}_t$ is obtained from the GDFM.

The first statistic, (18), represents the noise-to-signal ratio; that is, the larger *NS(j)* is, the more departed are the observed variables from the latent factors. In the extreme case, if the $\hat{\mathbf{y}}(j)$ is exactly the same as the latent factors, then *NS(j)* is equal to zero. The second statistic, (19), is simply the coefficient of determination. If $R^2(j)$ is one, then the individual observed variables is an exact latent factor. For the second statistic to be meaningful, it is important to obtain a confidence interval for $R^2(j)$. The upper and lower confidence interval is given by:

$$\left(R_j^{2+}, R_j^{2-}\right) = \left(R_j^2 + 2*1.96\frac{2\left|R_j\right|\left(1-R_j^2\right)}{\sqrt{T}}, R_j^2 - 2*1.96\frac{2\left|R_j\right|\left(1-R_j^2\right)}{\sqrt{T}}\right) \quad (20)$$

The results of the proposed two statistics are summarized by sector in table 2.3. The detailed results for the individual variables are given in table 2.4. Many surprising features emerge from table 2.3. First of all, it is easy to see that nominal variables (such as nominal effective exchange rates, monetary aggregates, and consumer prices) are strong proxies for the latent factors. Specifically, the nominal effective exchange rates shocks have the strongest relations with the unobserved common factors, where *NS* and R^2 are 0.17 and 85%, respectively. Similarly, the consumer prices in the GCC area and the consumer prices in foreign economies appear to have strong relation to the latent factors. Second, the GCC GDP is also a good proxy of the latent factors with R^2 around 55%. Finally, exports and oil productions unexpectedly are not good proxies for the latent factors. This puzzling result comes from the fact that the GCC area is comprised of natural-resource-based economies; therefore, it is expected that real shocks ought to play a vital role in the business cycle fluctuations. However, there is hardly any evidence of strong relation between oil productions and latent factors.

The previous results imply that the main source of economic fluctuations in the panel of macroeconomic variables is the nominal shocks. These nominal shocks appear to be more important than real shocks in explaining the driving forces of business cycle evolutions in the GCC area.

2.7 Conclusion

By commencing a single currency in the Gulf Cooperation Council (GCC) area in 2010, policymakers at the prospective supernational monetary agency will construct a common monetary policy based on the GCC-wide economic developments. Having timely information about the development of the GCC business cycle is invaluable for the policymakers. Since the GDP data is released with considerable lag and contains measurement errors and seasonal effects, constructing a smoother and timely indicator of the GCC business cycle can be a good analytical and empirical tool for the policymakers and the business community. It provides a clear signal about the underlying movement of the GCC area economy. The coincident indicator is constructed by utilizing the Generalized Dynamic Factor Model (GDFM) proposed by Forni *et al.* (2000, 2004, and 2005), and applied to the Euro area by Altissimo *et al.* (2001). The GDFM is applied to a quarterly dataset with 82 economic variables from 1980 to 2007.

The results suggest that as few as three common shocks can be sufficient in explaining business cycle developments for the GCC area. The constructed coincident indicator closely resembles the movement in the GCC GDP growth, especially for the last ten years, pointing to a higher degree of commonality across the GCC economies. As a by-product of utilizing the GDFM, a higher degree of commonality is found within nominal effective exchange rates, exports, imports, oil prices, oil productions, consumer prices, and monetary aggregates, since those variables are closely related to the GCC GDP (which depends to a great extent on oil income).

The direction and timing of economic variables is mixed. While oil prices, consumer prices, exports, imports, and oil productions are pro-cyclical with respect to the coincident indicator, nominal effective exchange rates behave in the opposite way to the reference cycle. Further, in accordance with the economic theory, financial variables such as exchange rates, interest rates, and yield spreads are classified as leading variables with respect to the reference cycle, which reflect the expectation of the future economic outcomes. On the other hand, a high proportion of the lagging variables are found within consumer prices and imports. This result suggests that some nominal frictions, such as price stickiness, exist in the GCC area.

Finally, to test the economic meaningfulness of the statistically latent factors, the proposed test by Bai and Ng (2006) was applied to the GCC dataset. The results show that the nominal shocks are strong proxies for the latent factors. These nominal shocks appear to be more important than real shocks in explaining the driving forces of business cycle evolutions in the GCC area.

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Figure 2.1: Average dynamic eigenvalues over cross-sectional units

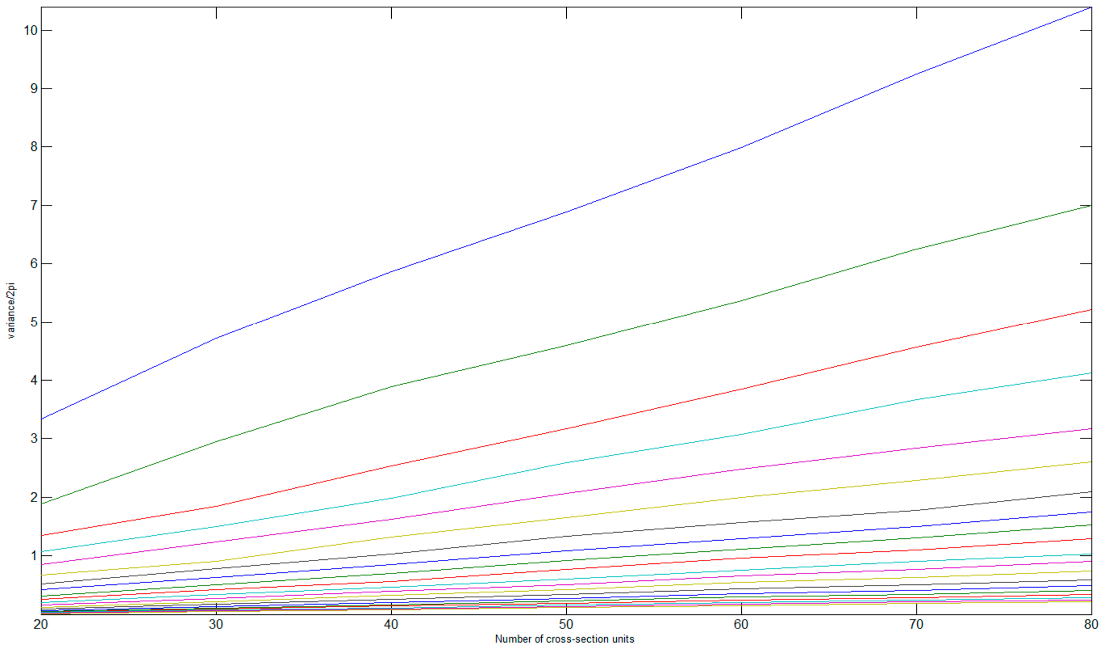

Figure 2.2: Percentage of variance explained

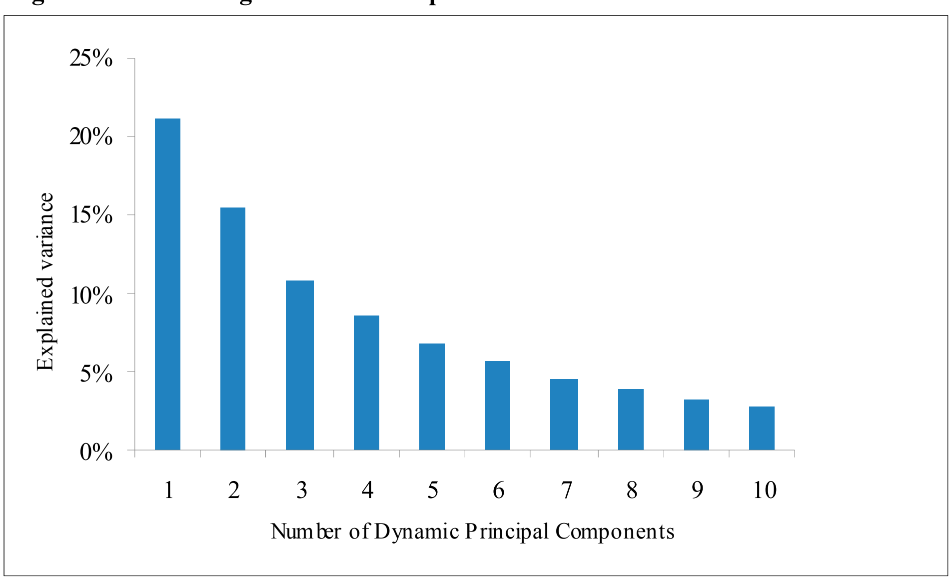

Figure 2.3: Spectral density functions of all eigenvalues

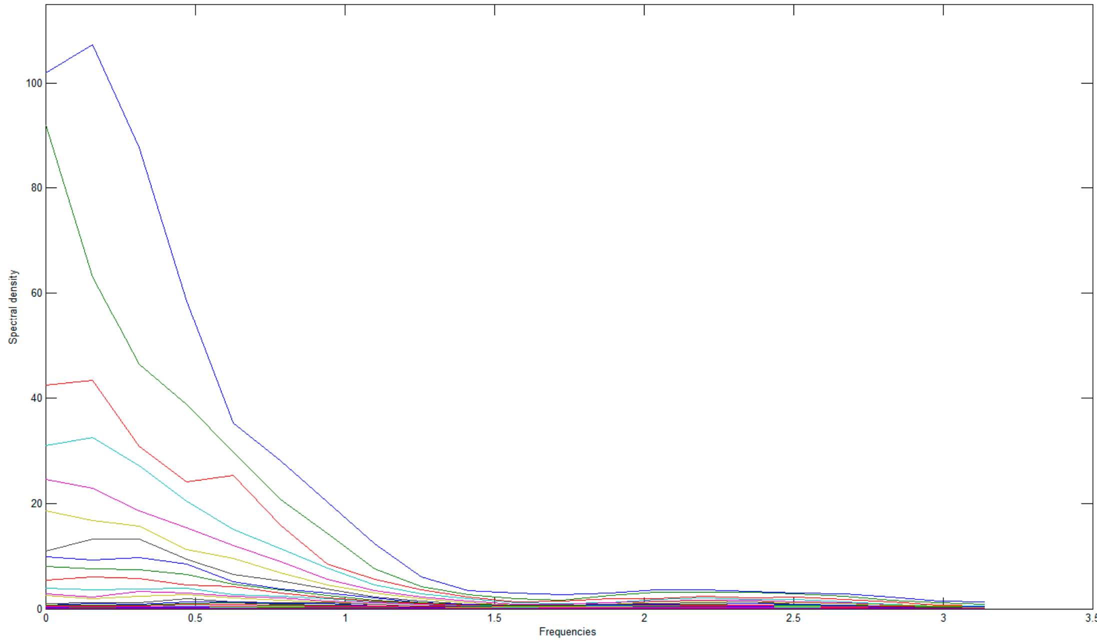

Figure 2.4: Average of spectral density functions

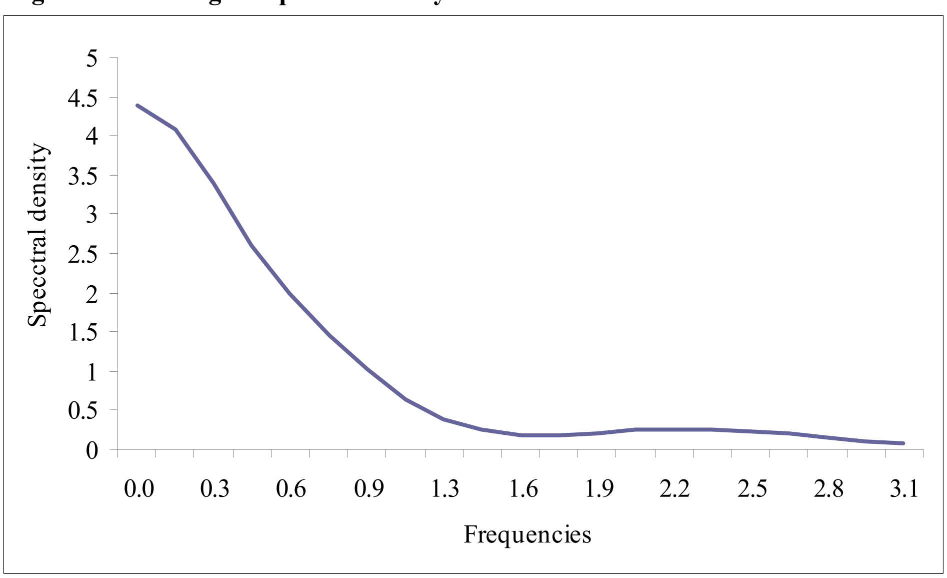

Figure 2.5: The GCC coincident indicator and the GCC area GDP growth rate

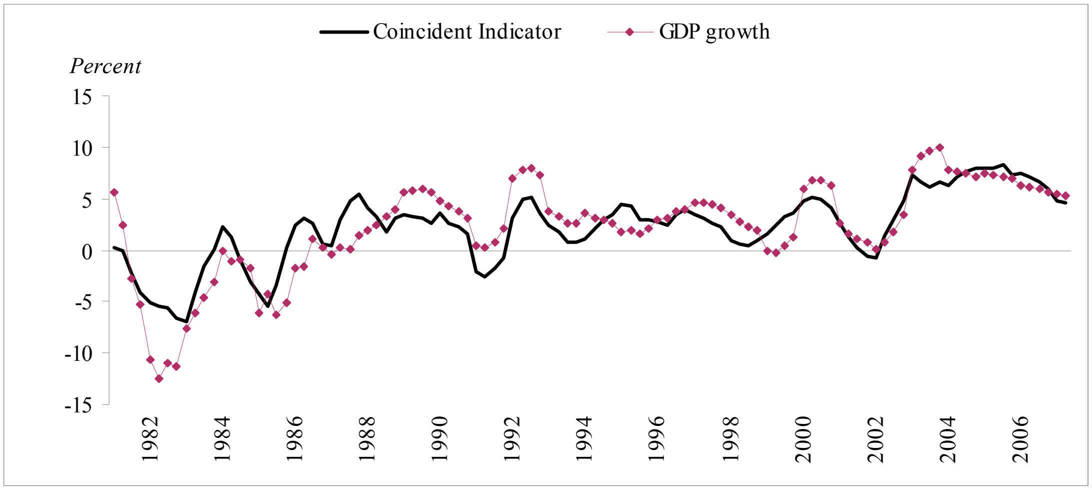

Figure 2.6: The GCC coincident indicator and the common component of national GDP growth

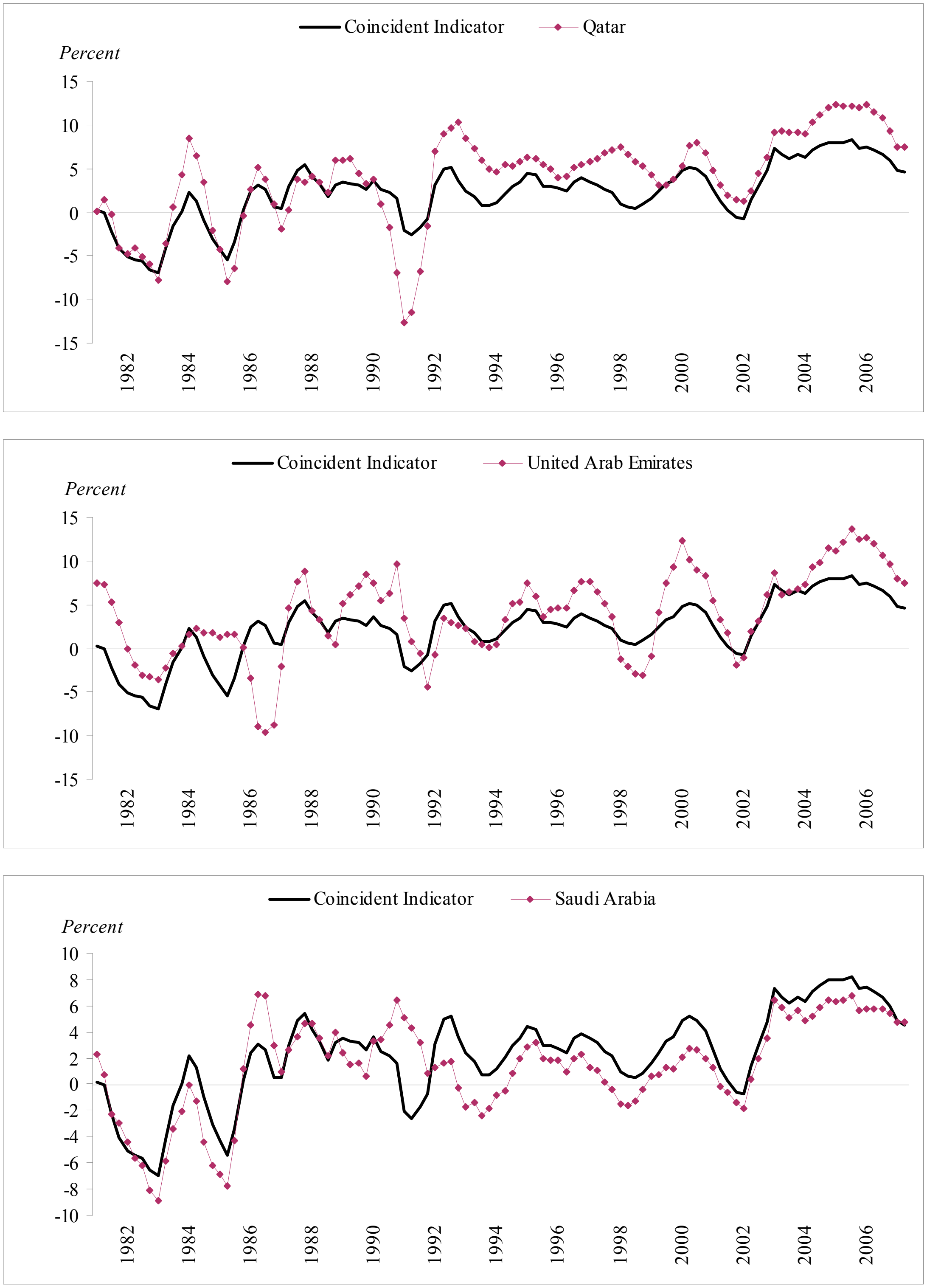

Figure 2.6: The GCC coincident indicator and the common component of national GDP growth

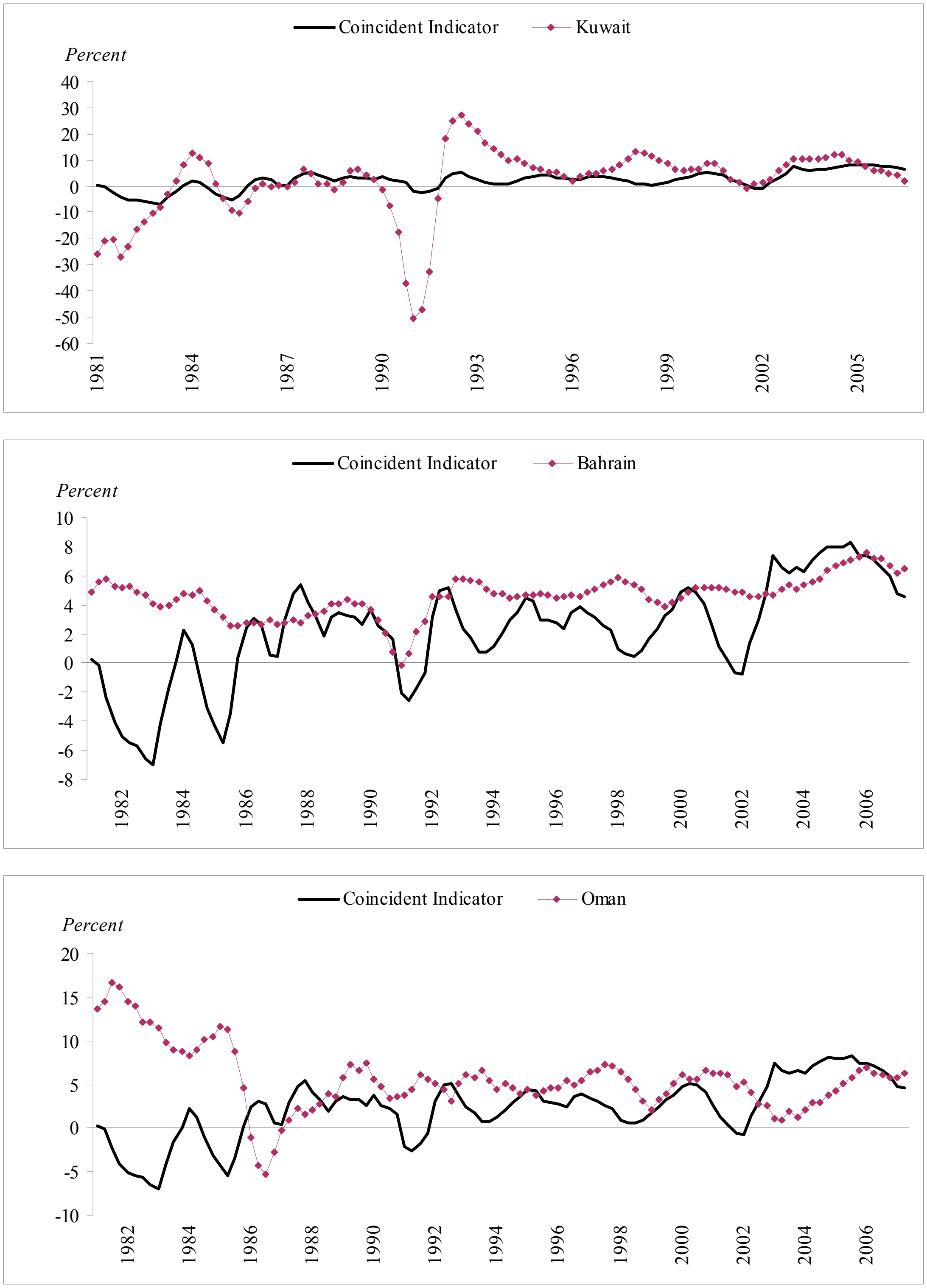

Table 2.1: Data, degree of commonality, and cyclical behavior

Country	Descriptor	Commonality	Phase	Time lag
GCC	Real Gross Domestic Product	0.57	0.00	(0.00)
BHR	Real Gross Domestic Product	0.21	0.00	(0.84)
KWT	Real Gross Domestic Product	0.53	0.00	(0.14)
OMN	Real Gross Domestic Product	0.49	3.14	(1.87)
QTR	Real Gross Domestic Product	0.36	0.00	0.01
KSA	Real Gross Domestic Product	0.44	0.00	0.07
UAE	Real Gross Domestic Product	0.36	0.00	(0.01)
BHR	Nominal Effective Exchange Rate	0.53	3.14	2.16
OMN	Nominal Effective Exchange Rate	0.51	3.14	2.36
QTR	Nominal Effective Exchange Rate	0.48	3.14	2.16
KSA	Nominal Effective Exchange Rate	0.46	3.14	2.34
UAE	Nominal Effective Exchange Rate	0.50	3.14	2.17
BHR	Consumer Price Index 2000=100	0.42	3.14	(1.88)
KWT	Consumer Price Index 2000=100	0.50	3.14	(1.86)
OMN	Consumer Price Index 2000=100	0.30	0.00	(0.78)
QTR	Consumer Price Index 2000=100	0.46	0.00	(0.41)
KSA	Consumer Price Index 2000=100	0.23	0.00	(1.02)
UAE	Consumer Price Index 2000=100	0.27	0.00	(0.62)
	Average Oil Prices	0.38	0.00	(0.74)
BHR	Money plus Quasi-Money	0.22	3.14	(2.01)
KWT	Money plus Quasi-Money	0.51	3.14	2.01
OMN	Money plus Quasi-Money	0.59	3.14	2.47
QTR	Money plus Quasi-Money	0.37	0.00	1.53
KSA	Money plus Quasi-Money	0.53	3.14	(1.46)
UAE	Money plus Quasi-Money	0.45	3.14	(0.73)
BHR	Foreign Assets (Net)	0.36	3.14	0.85
KWT	Foreign Assets (Net)	0.22	3.14	1.45
OMN	Foreign Assets (Net)	0.33	3.14	(2.31)
QTR	Foreign Assets (Net)	0.20	0.00	1.28
KSA	Foreign Assets (Net)	0.64	0.00	(0.23)
UAE	Foreign Assets (Net)	0.25	3.14	(0.19)
BHR	Claims on Private Sector	0.38	0.00	(0.45)
KWT	Claims on Private Sector	0.30	3.14	1.76
OMN	Claims on Private Sector	0.28	3.14	2.17
QTR	Claims on Private Sector	0.26	0.00	(0.98)
KSA	Claims on Private Sector	0.39	0.00	(0.39)
UAE	Claims on Private Sector	0.56	0.00	(0.50)
BHR	Total International Reserves	0.30	3.14	0.61
KWT	Total International Reserves	0.16	3.14	2.07
OMN	Total International Reserves	0.22	0.00	2.50
QTR	Total International Reserves	0.18	0.00	0.17
KSA	Total International Reserves	0.11	0.00	(0.17)
UAE	Total International Reserves	0.16	0.00	0.54
BHR	Exports	0.38	0.00	(0.19)
KWT	Exports	0.54	0.00	(0.58)
OMN	Exports	0.34	0.00	0.33
QTR	Exports	0.33	0.00	(0.31)

Country	Descriptor	Commonality	Phase	Time lag
KSA	Exports	0.52	0.00	(0.14)
UAE	Exports	0.51	0.00	(0.05)
BHR	Imports	0.39	0.00	(0.51)
KWT	Imports	0.43	0.00	(1.40)
OMN	Imports	0.36	0.00	0.24
QTR	Imports	0.26	0.00	(1.29)
KSA	Imports	0.32	0.00	(1.30)
UAE	Imports	0.24	0.00	(1.81)
BHR	Crude Petroleum Production Index 2000=100	0.27	0.00	0.23
KWT	Crude Petroleum Production Index 2000=100	0.42	0.00	0.09
OMN	Crude Petroleum Production Index 2000=100	0.26	3.14	1.03
QTR	Crude Petroleum Production Index 2000=100	0.32	0.00	(0.20)
KSA	Crude Petroleum Production Index 2000=100	0.47	0.00	0.04
UAE	Crude Petroleum Production Index 2000=100	0.34	0.00	0.45
KWT	Oil production	0.49	0.00	(1.15)
QTR	Oil production	0.30	0.00	(0.61)
KSA	Oil production	0.47	0.00	(0.13)
UAE	Oil production	0.34	0.00	(0.36)
Japan	Real Gross Domestic Product	0.22	3.14	0.81
U.S.	Real Gross Domestic Product	0.37	3.14	0.45
EU 15	Real Gross Domestic Product	0.19	0.00	1.86
Japan	Consumer Price Index 2000=100	0.41	3.14	1.45
U.S.	Consumer Price Index 2000=100	0.46	3.14	2.07
EU 15	Consumer Price Index 2000=100	0.51	3.14	(2.39)
U.S.	Treasury Bill	0.35	0.00	0.03
U.S.	Government yield spread	0.18	3.14	2.49
U.S.	Corporate yield spread	0.14	3.14	2.43
GCC	Deposit rate	0.26	0.00	0.28
GCC	Lending rate	0.15	0.00	(0.23)
BHR	Claims on Central Government (Net)	0.15	0.00	(1.51)
KWT	Claims on Central Government (Net)	0.27	3.14	(0.93)
OMN	Claims on Central Government (Net)	0.28	3.14	0.81
QTR	Claims on Central Government (Net)	0.29	3.14	1.94
KSA	Claims on Central Government (Net)	0.64	3.14	1.43
UAE	Claims on Central Government (Net)	0.16	3.14	(1.95)

1) GCC is the Gulf Cooperation Council, BHR is Bahrain, KWT is Kuwait, OMN is Oman, QTR is Qatar, KSA is the Kingdom of Saudi Arabia, and UAE is the United Arab Emirates.
2) The commonality of any time series is the relative ratio of its common component variance to its total variance.
3) Phase determines the direction of the time series with respect to the reference cycle. The time series is pro-cyclical if the phase is equal zero, otherwise it is counter-cyclical.
4) The variable is lagging if time lag < -1, leading > 1, otherwise coincident.

Table 2.2: The direction and timing of variables against the coincident indicator

Variable	Direction	Timing
Industrial Production	Pro-cyclical	Coincident
Domestic GDP	Pro-cyclical	Coincident
Foreign GDP		
Euro area	Pro-cyclical	Leading
U.S.	Counter-cyclical	Coincident
Financial Variables		
Interest rates	Pro-cyclical	Coincident
Yield spread	Counter-cyclical	Leading
Nominal effective exchange rates	Counter-cyclical	Leading
Prices		
GCC consumer prices	Pro-cyclical	Lagging & coincident
Real oil prices	Pro-cyclical	coincident
Monetary Aggregates		
Money supply	Counter-cyclical	Leading
Net claim on government	Counter-cyclical	Leading
Total international reserves	Pro-cyclical	Coincident
International trade		
Exports	Pro-cyclical	Coincident
Imports	Pro-cyclical	Lagging

Table 2.3: Testing the observed macroeconomic data against the latent factors

Descriptor	***NS(j)***	$R^2(j)$
Nominal Effective Exchange rates	0.17	85%
GCC GDP	0.82	55%
Europe CPI	0.86	54%
US CPI	1.21	45%
Money Supply	2.43	34%
Net Foreign Assets	2.97	32%
Japan CPI	2.18	31%
Consumer Prices	2.74	31%
US GDP	2.30	30%
Exports	4.01	25%
Oil Prices	3.29	23%
Treasury Bill	3.64	22%
Net Claim on Central Governments	7.16	20%
Interest rates	6.72	16%
Total Reserves	7.27	16%
U.S. government yield spread	5.60	15%
EU 15 GDP	7.22	12%
Imports	10.84	12%
Oil Productions	9.01	11%
Japan GDP	39.46	2%
corporate yield spread	44.30	2%

*The statistics in this table are the average results by sector for individual time series.

Table 2.4: Testing the observed individual macroeconomic variables against the latent factors

Country	Descriptor	NS	$R^2(j)$	$R^{2+}(j)$	$R^{2-}(j)$
GCC	Real Gross Domestic Product	0.82	55%	67%	42%
BHR	Real Gross Domestic Product	7.16	12%	24%	1%
KWT	Real Gross Domestic Product	2.82	26%	40%	12%
OMN	Real Gross Domestic Product	1.66	38%	52%	23%
QTR	Real Gross Domestic Product	3.18	24%	38%	10%
KSA	Real Gross Domestic Product	3.01	25%	39%	11%
UAE	Real Gross Domestic Product	2.62	28%	42%	13%
BHR	Nominal Effective Exchange Rate	0.16	86%	91%	82%
OMN	Nominal Effective Exchange Rate	0.17	86%	91%	81%
QTR	Nominal Effective Exchange Rate	0.19	84%	89%	78%
KSA	Nominal Effective Exchange Rate	0.18	85%	90%	79%
UAE	Nominal Effective Exchange Rate	0.16	86%	91%	81%
BHR	Consumer Price Index 2000=100	2.44	29%	43%	15%
KWT	Consumer Price Index 2000=100	2.88	26%	40%	12%
OMN	Consumer Price Index 2000=100	2.72	27%	41%	13%
QTR	Consumer Price Index 2000=100	0.91	52%	65%	39%
KSA	Consumer Price Index 2000=104	5.79	15%	27%	2%
UAE	Consumer Price Index 2000=100	1.72	37%	51%	22%
	Average Oil Prices	3.29	23%	37%	9%
BHR	Money plus Quasi-Money	30.21	3%	10%	0%
KWT	Money plus Quasi-Money	1.64	38%	52%	24%
OMN	Money plus Quasi-Money	0.93	52%	65%	39%
QTR	Money plus Quasi-Money	4.56	18%	31%	5%
KSA	Money plus Quasi-Money	1.54	39%	54%	25%
UAE	Money plus Quasi-Money	3.50	22%	36%	8%
BHR	Foreign Assets (Net)	2.84	26%	40%	12%
KWT	Foreign Assets (Net)	6.56	13%	25%	1%
OMN	Foreign Assets (Net)	2.46	29%	43%	15%
QTR	Foreign Assets (Net)	10.81	8%	18%	0%
KSA	Foreign Assets (Net)	0.66	60%	72%	49%
UAE	Foreign Assets (Net)	2.31	30%	45%	16%
BHR	Claims on Private Sector	5.52	15%	28%	3%
KWT	Claims on Private Sector	17.22	5%	14%	0%
OMN	Claims on Private Sector	4.07	20%	33%	6%
QTR	Claims on Private Sector	6.70	13%	25%	1%
KSA	Claims on Private Sector	2.98	25%	39%	11%
UAE	Claims on Private Sector	2.26	31%	45%	16%
BHR	Total International Reserves	5.53	15%	28%	3%
KWT	Total International Reserves	12.52	7%	17%	0%

Country	Descriptor	NS	$R^2(j)$	$R^{2+}(j)$	$R^{2-}(j)$
OMN	Total International Reserves	2.68	27%	41%	13%
QTR	Total International Reserves	8.77	10%	21%	0%
KSA	Total International Reserves	11.25	8%	18%	0%
UAE	Total International Reserves	2.85	26%	40%	12%
BHR	Exports	3.18	24%	38%	10%
KWT	Exports	8.44	11%	22%	0%
OMN	Exports	19.09	5%	13%	0%
QTR	Exports	5.08	16%	29%	4%
KSA	Exports	1.53	40%	54%	25%
UAE	Exports	1.82	35%	50%	21%
BHR	Imports	2.80	26%	41%	12%
KWT	Imports	20.90	5%	12%	0%
OMN	Imports	5.53	15%	28%	3%
QTR	Imports	11.39	8%	18%	0%
KSA	Imports	7.97	11%	22%	0%
UAE	Imports	16.46	6%	14%	0%
BHR	Crude Petroleum Production Index 2000=100	12.57	7%	17%	0%
KWT	Crude Petroleum Production Index 2000=100	6.90	13%	24%	1%
OMN	Crude Petroleum Production Index 2000=100	65.41	2%	6%	0%
QTR	Crude Petroleum Production Index 2000=100	3.97	20%	34%	7%
KSA	Crude Petroleum Production Index 2000=100	5.54	15%	28%	3%
UAE	Crude Petroleum Production Index 2000=100	12.55	7%	17%	0%
KWT	Oil production	8.19	11%	22%	0%
QTR	Oil production	4.99	17%	29%	4%
KSA	Oil production	8.39	11%	22%	0%
UAE	Oil production	14.47	6%	15%	0%
Japan	Real Gross Domestic Product	39.46	2%	8%	0%
US	Real Gross Domestic Product	2.30	30%	45%	16%
EU 15	Real Gross Domestic Product	7.22	12%	24%	1%
Japan	Consumer Price Index 2000=100	2.18	31%	46%	17%
US	Consumer Price Index 2000=100	1.21	45%	59%	31%
EU 15	Consumer Price Index 2000=100	0.86	54%	67%	41%
US	Treasury Bill	3.64	22%	35%	8%
US	Government yield spread	5.60	15%	28%	3%
US	Corporate yield spread	44.30	2%	8%	0%
GCC	Deposit rate	3.43	23%	36%	9%
GCC	Lending rate	10.00	9%	19%	0%
BHR	Claims on Central Government	7.28	12%	24%	0%
KWT	Claims on Central Government	9.13	10%	21%	0%
OMN	Claims on Central Government	3.55	22%	36%	8%

Country	Descriptor	NS	$R^2(j)$	$R^{2+}(j)$	$R^{2-}(j)$
QTR	Claims on Central Government	5.96	14%	27%	2%
KSA	Claims on Central Government	0.78	56%	69%	44%
UAE	Claims on Central Government	16.26	6%	14%	0%

1) GCC is the Gulf Cooperation Council, BHR is Bahrain, KWT is Kuwait, OMN is Oman, QTR is Qatar, KSA is the Kingdom of Saudi Arabia, and UAE is the United Arab Emirates.
2) *NS(J)* is the noise-to-signal ratio.

3) $R^2(j)$ is the coefficient of determination. $R^{2+}(j)$ and $R^{2-}(j)$ are the upper and lower confidence interval of that coefficient.

Chapter 3: A Small Open Economy DSGE Model for the GCC Area

3.1 Introduction

Motivated by the creation of a monetary union in the GCC area[19] in 2010 and the implementation of a single monetary policy in 2010, there has been an increased interest in academic and policy circles regarding the determinants of business cycle fluctuations in the GCC area. As a result of this prospective monetary union, a common monetary policy will be based on GCC area-wide economic developments. In this chapter, I layout a Dynamic Stochastic General Equilibrium Model (DSGE) for a small open economy with a fixed exchange rate regime for the GCC area. I then discuss the qualitative aspects of the model of different exogenous economic shocks in order to assess the business cycle evolution of the GCC area. The model derived in this chapter belongs to the New Open Economy Macroeconomics (NOEM) literature, which examines the interaction among open economies with well-specified microeconomic foundations. Unlike the traditional reduced-form macroeconomics models, such as Vector Autoregressive (VAR) models, the DSGE models' parameters have a structural interpretation which avoids the Lucas critique (1976).[20]

Much of the development in the general equilibrium models involves the introduction of nominal rigidities and imperfect competition into the DSGE models. These frictions have been introduced by the New Keynesian theorists to account for dynamic persistence observed in many macroeconomic variables. If nominal rigidities

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[19] The Gulf Cooperation Council (GCC) consists of six member countries: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates. On November 2006, Oman indicated that it may not be able to join the monetary union by 2010 because it cannot meet some of the convergence criteria due to massive infrastructure projects.

[20] "Lucas argued that economic theory predict that the decision rules for investment, consumption, and expectations formation will not be invariant to shifts in the systematic behavior of policy" (Walsh, 2003)

can account for the dynamics of macroeconomic variables, then monetary policy can be used as a tool to stabilize real economic variables. The version of the model outlined in this chapter is based on the seminal work of Obstfeld and Rogoff (1995). However, it includes many nominal and real rigidities of closed economic models introduced by Altig *et al*. (2005), Christiano *et al*. (2005), and Smets and Wouter (2003). Examples of nominal and real rigidities include price stickiness, habit persistence in consumption, capital adjustment costs, and incomplete exchange rate pass-through. In accordance with common contemporary practices of most central banks, I model the monetary aggregates as endogenous variables and the short-term interest rate as the monetary policy instrument. Finally, I use the model to analyze the effects of exogenous shocks on macroeconomic variables from a general equilibrium perspective.

Erceg *et al*. (2006) mention some benefits of using the DSGE framework over reduced-form models or large-scale econometric models. One key advantage of utilizing the DSGE framework is that it clearly assesses the linkage of economic structural features. For instance, it may be of interest to examine how the effectiveness of the tax cut depends on the elasticity of labor demand. It is very difficult to conduct such an experiment in a reduced-form model or a large-scale model since there is no clear link between structural and reduced-form parameters. Moreover, after observing the initial shocks, the DSGE models clearly describe the mechanisms through which the economy returns to its balanced growth path. That is, if there is a productivity shock, then the DSGE models can illustrate the economic forces that cause trade balance to move from trade deficit to surplus and how different initial assumptions about the underlying shock result in different adjustment dynamics.

The small open economy model applied in this chapter is a two-country model: the GCC area is the home economy and the rest of the world is the foreign economy. The model can be used to examine the interaction between these two economies in cases where the economic developments in one economy may affect the other. This model is meant to characterize the relatively small GCC economies where economic developments have little or no impact at all on the world economy. Thus, as a limiting case, it is reasonable to treat foreign output, inflation, and interest rate as exogenous variables to the GCC area.

The contribution of this chapter as follows: first of all, to my knowledge, it is the first attempt to layout a DSGE model for the GCC area. Second, the model can be used by policymakers at the prospective GCC supernational monetary agency and fiscal authorities to examine the dynamic effects of exogenous shocks on endogenous macroeconomic variables and understand the sources of business cycle fluctuations. Thus, it facilitates the formulation of optimal monetary and fiscal policies for the GCC region. Finally, the DSGE model can serve as a "workhorse" for macroeconomic analysis of the GCC economy. The DSGE model presented in this chapter is simulated in order to examine the dynamic impact of exogenous shocks on aggregate output and inflation. However, estimating or calibrating structural parameters of the model is left for future research when data become available, where the model can be used to extract historical shocks, obtain variance decomposition, and forecast key macroeconomic variables of interest.

The remainder of this chapter is organized as follows: section 3.2 gives an overview of the DSGE Model; section 3.3 simulation and dynamic of the model; section 3.4 concludes.

3.2 Model

The model is a two-country small open economy. The world is inhabited by a continuum of infinite-lived households. Each household lives either in a home country or a foreign country. I assume the GCC area to be the home country and denote it by the subscript *H*, and the "rest of the world" to be the foreign country, which is denoted by the subscript *F*. In this section, I sketch the derivation of key structural equations implied by the model. Those equations have some similarities to the ones proposed by Christiano *et al*. (2005), Smets and Wouters (2003), Adolfson *et* *al.* (2007), and Altig *et al.* (2005). In particular, the model is closely related to the one in Medina and Soto (2006a, b).

The utility function of each household is defined over a composite of consumption goods and real money balances. In contrast with literatures on closed economy models, the composite consumption goods presented here consist of both domestic and foreign produced goods. There is habit persistence in the consumption preference. Each household can invest in state-contingent domestic bonds and/or foreign bonds.

There are three sectors in the home economy: a domestic sector, an importing sector, and an oil sector. The domestic sector produces differentiated intermediate goods using capital and labor which are then sold to domestic final goods firms. The importing sector distributes foreign intermediate goods to domestic final goods firms. The domestic and importing intermediate firms have monopoly power and set their prices in a staggered way. Furthermore, both the domestic and foreign intermediate goods are transformed by final goods firms to final home goods, which are then consumed by households, the government, and/or used to accumulate more capital stock. Finally, the output of the oil sector is completely exported abroad, and this sector is totally owned by the government.

With regard to monetary policy, since there is an almost perfect peg of GCC currencies with respect to the U.S. dollar, the monetary policy will respond one-to-one with the foreign interest rate.

3.2.1 Households

There is a continuum of infinite-lived households in the home country, denoted by $j \in (0,1)$. All households have identical preferences and initial wealth. With a complete financial market assumption, we can focus on the optimization problem of a representative household in the home country[21]. The preferences of the representative household are defined across a composite of consumption goods and real money balances[22]. Each household j maximizes the expected present discounted value of the Constant Relative Risk Aversion (CRRA) utility function:

$$E_0^j \sum_{t=0}^{\infty} \beta^t \left[\frac{\zeta_t^c}{1-\sigma_c} (C_t^j - hC_{t-1})^{1-\sigma_c} + \frac{\zeta_t^M}{1-\sigma_m} \left(\frac{M_t^j}{P_t} \right)^{1-\sigma_m} \right] \tag{1}$$

where C_t^j and $\frac{M_t^j}{P_t}$ denote the j^{th} household's level of aggregate consumption and real cash balances, respectively. σ_c is the coefficient of relative risk aversion and σ_m is the inverse of the elasticity of money holding with respect to interest rate. Finally, ζ_t^c represents a preference shock (demand shock) and ζ_t^M represents a shock to money demand. As usual, I assume that $0 < \beta < 1$, $0 \le h \le 1$, $\sigma_c > 0$, and $\sigma_m > 0$.

I follow Smets and Wouters (2003) by assuming a habit formation in consumption, where hC_{t-1} is the external habit stock at time *t.* The external habit stock is proportional to the last period aggregate consumption level that is exogenous to each representative household. Thus, each household cares about its consumption relative to the aggregate last period per capita consumption of optimizing households.

The aggregate consumption at time *t* is defined as a Constant Elasticity of Substitution (CES) composite consumption index of domestically produced (*home goods*) and imported (*foreign goods*) consumption goods according to:

$$C_t = \left[\gamma_c^{\frac{1}{\eta_c}} (C_{H,t})^{\frac{\eta_c - 1}{\eta_c}} + (1-\gamma_c)^{\frac{1}{\eta_c}} (C_{F,t})^{\frac{\eta_c - 1}{\eta_c}} \right]^{\frac{\eta_c}{\eta_c - 1}} \tag{2}$$

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[21] Households are Ricardian; i.e. they can intertemporally smooth consumption through full access to the capital markets.

[22] The labor supply is not present in the utility function, because I assume the labor supply is inelastic. That is, the number of labor hours is determined by the intermediate goods firms.

where η_c is the intertemporal elasticity of substitution between a basket of domestically produced consumption goods $\left(C_{H,t}\right)$ and a basket of imported consumption goods $\left(C_{F,t}\right)$. The share of imported consumption goods in the home consumption expenditure is denoted by $(1-\gamma_c)$. I assume that $\eta_c > 1$ and $\gamma_c \in [0,1]$. The variables $C_{H,t}$ and $C_{F,t}$ in (2) are defined respectively by the CES composite consumption indices:

$$\begin{aligned} C_{H,t} &= \left[\int_0^1 C_{H,t}(i)^{\frac{\varepsilon-1}{\varepsilon}} di\right]^{\frac{\varepsilon}{\varepsilon-1}} \\ C_{F,t} &= \left[\int_0^1 C_{F,t}(i)^{\frac{\varepsilon-1}{\varepsilon}} di\right]^{\frac{\varepsilon}{\varepsilon-1}} \end{aligned} \tag{3}$$

where $\varepsilon > 1$ is the price elasticity of demand for individual goods produced in a same country. $C_{H,t}(i)$ and $C_{F,t}(i)$ are the consumption levels of domestic and imported consumption goods *i*, respectively. The optimization problem of consumption expenditures can be written as:

$$\min_{C_{H,t},C_{F,t}} P_{H,t}C_{H,t} + P_{F,t}C_{F,t}$$

subject to total consumption:

$$C_t \le \left[\gamma_c^{\frac{1}{\eta_c}}(C_{H,t})^{\frac{\eta_c-1}{\eta_c}} + (1-\gamma_c)^{\frac{1}{\eta_c}}(C_{F,t})^{\frac{\eta_c-1}{\eta_c}}\right]^{\frac{\eta_c}{\eta_c-1}}$$

The optimal consumption allocation between home and foreign consumption goods is given by:

$$C_{H,t} = \gamma_c \left[\frac{P_t}{P_{H,t}}\right]^{\eta_c} C_t \tag{4}$$

$$C_{F,t} = (1-\gamma_c)\left[\frac{P_t}{P_{F,t}}\right]^{\eta_c} C_t \tag{5}$$

Where $P_{H,t}$ and $P_{F,t}$ are the home currency price indices of domestic and imported consumption goods sold in the home economy, respectively. P_t is the home country Consumer Price Index (CPI):

$$P_t = \left[\gamma_c (P_{H,t})^{1-\eta_c} + (1-\gamma_c)(P_{F,t})^{1-\eta_c} \right]^{\frac{1}{1-\eta_c}} \quad (6)$$

Intertemporal Budget Constraint

Since households behave as Ricardian consumers, each representative household in the home economy can invest in three types of financial assets: nominal money balance $\left(M_t^j\right)$, one-period non-contingent foreign bonds $\left(B_{F,t}^j\right)$ denominated in foreign currency, and one-period state-contingent domestic bonds $\left(B_{H,t}^j\right)$ denominated in domestic currency that pays one unit in a particular state. The intertemporal budget constraint of household *j* is given by:

$$M_t^j + P_t C_t^j + \frac{B_{H,t}^j}{(1+i_{H,t})} + \frac{e_t B_{F,t}^j}{(1+i_{F,t})\Theta} = M_{t-1}^j + B_{H,t}^j + e_t B_{F,t-1}^j + P_{H,t} W_t^j + \Pi_t^j + T_t^j \quad (7)$$

The left hand side of (7) represents how households use their resources, while the right hand side shows what resources the households have at their disposal. The variable $P_t C_t^j$ is nominal consumption expenditures, , $i_{H,t}$ is the domestic interest rate, e_t is the nominal exchange rate expressed in units of home currency per unit of foreign currency (i.e. a rise in e_t implies a depreciation of home currency), the term Θ is a constant premium on foreign bonds held by domestic households, $P_{H,t} W_t^j$ is the nominal labor income, Π_t^j is profit derived from investing in domestic firms, and T_t^j is per-capita lump sum net taxes.

Since there are a full set of state-contingent bonds, each household can insure against idiosyncratic risks. Therefore, we can preserve the representative agent framework by assuming that all households face the same budget constraints. The decision problem of the representative agent is to maximize the utility function with respect to consumption, money balances, investment in domestic firms, holdings of foreign bonds, and holdings of home state-contingent bonds subject to budget constraint. The following sets of equations are the first order conditions of the representative agent[23]:

$$\text{w.r.t } C_t: \ \frac{\xi_t^c}{\left(C_t - hC_{t-1}\right)} - \lambda_t P_t = 0$$

$$\text{w.r.t } B_{H,t}: \ \frac{-\lambda_t}{(1+i_{H,t})} - \beta\lambda_{t+1} = 0$$

$$\text{w.r.t } B_{F,t}: \ \frac{-\lambda_t e_t}{(1+i_{F,t})\Theta} + \beta\lambda_{t+1} e_{t+1} = 0$$

The optimal intertemporal allocation of home state-contingent bond is given by:

$$\beta E_t \left\{ (1+i_{H,t}) \frac{\xi_{t+1}^c}{\xi_t^c} \left(\frac{C_t - hC_{t-1}}{C_{t+1} - hC_t} \right) \frac{P_t}{P_{t+1}} \right\} = 1 \tag{8}$$

Similarly, the optimal allocation of foreign bonds is given by:

$$\beta E_t \left\{ (1+i_{F,t})\Theta \frac{\xi_{t+1}^c}{\xi_t^c} \left(\frac{C_t - hC_{t-1}}{C_{t+1} - hC_t} \right) \frac{e_{t+1}}{e_t} \frac{P_t}{P_{t+1}} \right\} = 1 \tag{9}$$

Finally, the Uncovered Interest Parity (UIP) condition can be derived by combining (8) and (9):

$$\left(1+i_{H,t}\right) = \left(1+i_{F,t}\right)\Theta E_t \left\{ \frac{e_{t+1}}{e_t} \right\} \tag{10}$$

3.2.2 Firms

(i) Domestic Firms

There are two types of domestic firms: intermediate and final goods firms. Intermediate goods are produced out of labor and capital, which then can be sold to final goods firms. Each intermediate firm has a monopoly power over its own goods and rents factor inputs from perfectly competitive markets. By contrast, final goods

[23] To simplify notation, the index j will be omitted since we are dealing with a representative agent.

are produced by transforming intermediate goods into homogenous final goods that are consumed by domestic households, the government, and/or used to accumulate more capital stock. The bundling process by the final goods firms are costless, where neither capital nor labor are used during the production process (e.g. repackaging or rebundling). The final goods are produced by perfectly competitive firms.

The home final goods are sold only in the domestic market $Y_{H,t}$. The final goods produced by a composite of a continuum differentiated intermediate goods according to the CES production technology:

$$Y_{H,t} = \left[\int_0^1 Y_{H,t}(z_H)^{\frac{\varepsilon_H - 1}{\varepsilon_H}} dz_H \right]^{\frac{\varepsilon_H}{\varepsilon_H - 1}} \tag{11}$$

where ε_H is the intertemporal elasticity of substitution among intermediate goods[24].

Each final good firm takes the output price and input prices as given. The profit maximization problem of each firm is given by:

$$\max_{Y_{H,t}(z_H)} P_{H,t} Y_{H,t} - \int_0^1 P_{H,t}(z_H) Y_{H,t}(z_H) dz_H$$

which can be written as:

$$\max_{Y_{H,t}(z_H)} P_{H,t} \left[\int_0^1 Y_{H,t}(z_H)^{\frac{\varepsilon_H - 1}{\varepsilon_H}} dz_H \right]^{\frac{\varepsilon_H}{\varepsilon_H - 1}} - \int_0^1 P_{H,t}(z_H) Y_{H,t}(z_H) dz_H$$

The first order condition of the final good sector is given by:

$$Y_{H,t}(z_H) = \left(\frac{P_{H,t}}{P_{H,t}(z_H)} \right)^{\varepsilon_H} Y_{H,t} \tag{12}$$

where $Y_{H,t}(z_H)$ represents the demand of a particular intermediate variety z_H and $P_{H,t}(z_H)$ denotes its price. By substituting (12) in (11), we obtain the aggregate producer price index, $P_{H,t}$:

[24] The purpose of using ε_H is to make the production function display a constant return to scale.

$$P_{H,t}=\left[\int_0^1 P_{H,t}(z_H)^{1-\varepsilon_H}\,dz_H\right]^{\frac{1}{1-\varepsilon_H}} \tag{13}$$

With regard to intermediate goods, each z_H is produced by a monopolist who maximizes profits by choosing its price subject to both the corresponding demands (12) and the following production function:

$$Y_{H,t}(z_H)=A_{H,t}\left[\alpha^{\frac{1}{\theta_H}}K_t(z_H)^{\frac{\theta_H-1}{\theta_H}}+(1-\alpha)^{\frac{1}{\theta_H}}\left(l_t(z_H)\right)^{\frac{\theta_H-1}{\theta_H}}+\right]^{\frac{\theta_H}{\theta_H-1}} \tag{14}$$

where $Y_{H,t}(z_H)$ is the total amount produced of intermediate goods z_H, $l_t(z_H)$ is the amount of labor used to produce z_H at real wage rate W_t, $K_t(z_H)$ is the amount of physical capital rented at real rental price of capital R_t, $A_{H,t}$ is the total factor productivity, and θ_H is the elasticity of substitution between labor and capital. Finally, α denotes the share of labor in the production function[25].

While each intermediate firm chooses how much quantity to produce, it cannot reset its prices in every period. The price setting problem of intermediate firms is similar to the one in Calvo (1983). That is, each intermediate firm faces a random probability $(1-\phi_H)$ of being able to re-optimize its price in any given period and the probability of receiving this signal is independent of past history. When setting their prices, intermediate firms take into account the probability ϕ_H that they will not be able to re-optimize in the future. Those intermediate firms which cannot re-optimize during period *t* through *t+i* update their prices according to the following rule-of-thumb:

$$P_{H,t+i}(z_H)=P_{H,t+i-1}(z_H) \tag{15}$$

Equation (15) implies that those intermediate firms keep their prices similar to the previous period. In contrast, when an intermediate firm receives a signal to re-

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[25] If $\theta_H=1$, equation (14) becomes Cobb-Douglas production function.

optimize its price in period *t*, it must choose the price $P^*_{H,t}(z_H)$ that solves the following optimization problem:

$$E_t \sum_{i=0}^{\infty} \beta^i \phi_H^i \left[P^*_{H,t}(z_H) \left(\frac{P_{H,t+i}}{P^*_{H,t}(z_H)} \right)^{\varepsilon_H} Y_{H,t+i} - P_{H,t+i} R_{t+i} K_{t+i}(z_H) - P_{H,t+i} W_{t+i} l_{t+i}(z_H) \right] \quad (16)$$

subject to the following production function:

$$Y_{H,t+i}(z_H) = \left(\frac{P_{H,t+i}}{P^*_{H,t}(z_H)} \right)^{\varepsilon_H} Y_{H,t+i} = A_{H,t+i} \left[K_{t+i}(z_H) \right]^{\alpha} \left[l_{t+i}(z_H) \right]^{1-\alpha}$$

The intermediate firm that maximizes the above optimization problem is also minimizing total costs. The following steps will first minimize total costs and then replace the minimum costs in the maximization problem (16). When a signal to reset its price is received, each intermediate firm chooses $K_{t+i}(z_H)$ and $l_{t+i}(z_H)$ to minimize the following real total costs:

$$R_{t+i} K_{t+i}(z_H) + W_{t+i} l_{t+i}(z_H) \quad (17)$$

subject to the following production function:

$$Y_{H,t+i}(z_H) = A_{H,t+i} \left[K_{t+i}(z_H) \right]^{\alpha} \left[l_{t+i}(z_H) \right]^{1-\alpha} \quad (18)$$

The first order conditions yields the following expression:

$$\frac{W_{t+i}}{R_{t+i}} = \left(\frac{(1-\alpha) K_{t+i}(z_H)}{\alpha \; l_{t+i}(z_H)} \right) \quad (19)$$

Solving (19) for $l_{t+i}(z_H)$ and then substituting the result in the production function yields:

$$K_{t+i}(z_H) = \frac{Y_{H,t+i}(z_H)}{A_{H,t+i}} \left(\frac{(1-\alpha) R_{t+i}}{\alpha \; W_{t+i}} \right)^{\alpha-1} \quad (20)$$

Similarly, Solving (19) for $K_{t+i}(z_H)$ and then substituting the result in the production function yields:

$$l_{t+i}(z_H) = \frac{Y_{H,t+i}(z_H)}{A_{H,t+i}} \left(\frac{(1-\alpha) R_{t+i}}{\alpha \; W_{t+i}} \right)^{\alpha} \quad (21)$$

Substituting (20) and (21) in the minimization problem gives:

$$\frac{W_{t+i}}{(1-\alpha)A_{H,t+i}}\left(\frac{(1-\alpha)R_{t+i}}{\alpha\ W_{t+i}}\right)^{\alpha} Y_{H,t+i}(z_H) \tag{22}$$

where the real marginal cost (*rmc*) is given by:

$$\frac{W_{t+i}}{(1-\alpha)A_{H,t+i}}\left(\frac{(1-\alpha)R_{t+i}}{\alpha\ W_{t+i}}\right)^{\alpha} \tag{23}$$

Finally, we substitute the minimized total real costs (22) into the profit maximization problem (16) to obtain:

$$E_t\sum_{i=0}^{\infty}\beta^i\phi_H^i\left[P_{H,t}^*(z_H)\left(\frac{P_{H,t+i}}{P_{H,t}^*(z_H)}\right)^{\varepsilon_H} Y_{H,t+i} - P_{H,t+i}\frac{W_{t+i}}{(1-\alpha)A_{H,t+i}}\left(\frac{(1-\alpha)R_{t+i}}{\alpha\ W_{t+i}}\right)^{\alpha} Y_{H,t+i}(z_H)\right]$$

or as:

$$E_t\sum_{i=0}^{\infty}\beta^i\phi_H^i\left[P_{H,t}^*(z_H)\left(\frac{P_{H,t+i}}{P_{H,t}^*(z_H)}\right)^{\varepsilon_H} Y_{H,t+i} - P_{H,t+i}\frac{W_{t+i}}{(1-\alpha)A_{H,t+i}}\left(\frac{(1-\alpha)R_{t+i}}{\alpha\ W_{t+i}}\right)^{\alpha}\left(\frac{P_{H,t+i}}{P_{H,t}^*(z_H)}\right)^{\varepsilon_H} Y_{H,t+i}\right]$$

which can be simplified to:

$$E_t\sum_{i=0}^{\infty}\beta^i\phi_H^i\left(\frac{P_{H,t+i}}{P_{H,t}^*(z_H)}\right)^{\varepsilon_H} Y_{H,t+i}\left[P_{H,t}^*(z_H)-\frac{P_{H,t+i}W_{t+i}}{(1-\alpha)A_{H,t+i}}\left(\frac{(1-\alpha)R_{t+i}}{\alpha\ W_{t+i}}\right)^{\alpha}\right]$$

The first order condition of the above optimization problem is given by:

$$E_t\sum_{i=0}^{\infty}(\beta\phi_H)^i\left(\frac{P_{H,t+i}}{P_{H,t}^*(z_H)}\right)^{\varepsilon_H} Y_{H,t+i}\left[(1-\varepsilon_H)+\frac{\varepsilon_H}{P_{H,t}^*(z_H)}\frac{P_{H,t+i}W_{t+i}}{(1-\alpha)A_{H,t+i}}\left(\frac{(1-\alpha)R_{t+i}}{\alpha\ W_{t+i}}\right)^{\alpha}\right]=0$$

Therefore, when the intermediate good firm receives a signal to re-optimize its price in period *t*, it reset its price to:

$$P_{H,t}^*(z_H)=\frac{\varepsilon_H}{\varepsilon_H-1}\frac{E_t\sum_{i=0}^{\infty}(\beta\phi_H)^i P_{H,t+i}Y_{H,t+i}(z_H)rmc_{t+i}}{E_t\sum_{i=0}^{\infty}(\beta\phi_H)^i Y_{H,t+i}(z_H)} \tag{24}$$

Since $\varepsilon_H > 1$, the re-optimized price is larger than the nominal marginal costs, which shows the monopolistic power of the intermediate good firms.

(ii) Importing Firms

The final foreign goods (Y_F) is produced by a composite of a continuum differentiated intermediate imported goods. It is then consumed by households and/or used to accumulate capital stock. It is produced according to CES technology:

$$Y_{F,t} = \left[\int_0^1 Y_{F,t}(z_F)^{\frac{\varepsilon_F - 1}{\varepsilon_F}} \right]^{\frac{\varepsilon_F}{\varepsilon_F - 1}} \tag{25}$$

Each final foreign goods firm takes the output and input prices as given. The profit maximization condition of the final foreign goods sector can be written as:

$$Y_{F,t}(z_F) = \left(\frac{P_{F,t}(z_F)}{P_{F,t}} \right)^{-\varepsilon_F} Y_{F,t} \tag{26}$$

Where $Y_{F,t}(z_F)$ is the demand of a particular intermediate imported variety z_H. $P_{F,t}(z_F)$ denotes the domestic currency price of imported variety z_H when used to produce goods for domestic market, while $P_{F,t}$ is the corresponding aggregate price of imported goods in the domestic market:

$$P_{F,t} = \left[\int_0^1 P_{F,t}(z_F)^{1-\varepsilon_F} dz_F \right]^{\frac{1}{1-\varepsilon_F}} \tag{27}$$

where the parameter ε_F is the intertemporal elasticity of substitution among intermediate imported goods.

To allow for incomplete exchange rate pass-through to import prices of consumption and investment goods, I assume local price stickiness[26]. That is, each

[26] The assumption of incomplete exchange-rate pass-through into import prices holds only in the short run. However, in the long run, the law-of-one-price will be prevailed when all importing firms can freely re-optimize their prices at any moment of time.

intermediate importing firm faces a random probability $(1-\phi_F)$ of being able to re-optimize its price in any given period, and the probability of receiving this signal is independent of past history. When setting their prices, intermediate import firms take into account the probability ϕ_F that they will not be able to re-optimize in the future. Those importing firms who cannot re-optimize during period t to $t+i$ update their prices according to the following rule-of-thumb:

$$P_{F,t+i}(z_F) = P_{F,t+i-1}(z_F) \tag{28}$$

Equation (28) implies those foreign intermediate firms keep their prices similar to the previous period. By contrast, when an intermediate importing firm receives a signal to re-optimize its price in period t, it must solve the following optimization problem:

$$E_t \sum_{i=0}^{\infty} \beta^i \phi_F^i \left[P_{F,t}^*(z_F) \left(\frac{P_{F,t+i}}{P_{F,t}^*(z_F)} \right)^{\varepsilon_H} Y_{F,t+i} - P_{F,t+i} R_{t+i} K_{t+i}(z_F) - P_{F,t+i} W_{t+i} l_{t+i}(z_F) \right]$$

Following the same procedure as in the previous section (ii), the optimal re-optimized price for each foreign intermediate good firm is:

$$P_{F,t}^*(z_F) = \frac{\varepsilon_F}{\varepsilon_F - 1} \frac{E_t \sum_{i=0}^{\infty} (\beta\phi_F)^i P_{F,t+i} Y_{F,t+i}(z_F) rmc_{t+i}}{E_t \sum_{i=0}^{\infty} (\beta\phi_F)^i Y_{F,t+i}(z_F)} \tag{29}$$

(iii) Oil Sector

There is only a single producing firm in this sector. The oil sector is fully owned by the government. It accounts for an average of 60% to 90% of the government budget in the GCC area and it is approximately 75% to 90% of the total exports in that region as well. The production function of the oil sector is given by:

$$Y_{S,t} = \left[Y_{S,t-1} \right]^{\rho_{y_s}} \left[Y_{S,0} \right]^{1-\rho_{y_s}} e^{\varepsilon_{ys,t}} \tag{30}$$

where $Y_{S,t}$ is the amount of oil production in period t, ρ_{y_s} is the persistence parameter, and $\varepsilon_{ys,t} \sim N(0, \sigma_{y_s}^2)$ represents a stochastic shock to the oil sector.

Although the oil industry is a highly capital-intense industry, most of the value added corresponds to rents associated to this scarce natural resource.

3.2.3 Investment and Capital Accumulation

Capital goods are rented to intermediate firms by a representative firm. The aggregate investment is defined as a CES composite investment index of domestic and imported goods according to:

$$I_t = \left[\gamma_I^{1/\eta_I} (I_{H,t})^{\frac{\eta_I - 1}{\eta_I}} + (1-\gamma_I)^{1/\eta_I} (I_{F,t})^{\frac{\eta_I - 1}{\eta_I}} \right]^{\frac{\eta_I}{\eta_I - 1}} \tag{31}$$

where η_I is the intertemporal elasticity of substitution between a basket of domestic goods $\left(I_{H,t}\right)$ and a basket of imported investment goods $\left(I_{F,t}\right)$ and γ_I is the share of domestic goods in home investment expenditures. I assume $\eta_I > 1$, and $0 < \gamma_I < 1$.

By maximizing (31) subject to $P_{I,t}\, I_t = P_{H,t}\, I_{H,t} + P_{F,t}\, I_{F,t}$, the optimal investment allocations of home and foreign investment goods are given by:

$$\begin{aligned} I_{H,t} &= \gamma_I \left[\frac{P_{I,t}}{P_{H,t}} \right]^{\eta_I} I_t \\ I_{F,t} &= (1-\gamma_I) \left[\frac{P_{I,t}}{P_{F,t}} \right]^{-\eta_I} I_t \end{aligned} \tag{32}$$

where $P_{H,t}$ and $P_{F,t}$ are the home currency prices of domestic and imported investment goods, respectively. $P_{I,t}$ is the home investment price index that is given by:

$$P_{I,t} = \left[\gamma_I P_{H,t}^{1-\eta_I} + (1-\gamma_I) P_{F,t}^{1-\eta_I} \right]^{\frac{1}{1-\eta_I}} \tag{33}$$

Each representative investment firm decides how much capital service to rent out to intermediate goods firms at a given rental rate Z_t. There is an adjustment cost for changing the investment plan. The representative firm chooses the investment plan that maximizes the following problem:

$$\max_{K_{t+s}, I_{t+s}} = E_t \left\{ \sum_{s=0}^{\infty} \nu^t \frac{R_{t+s} K_{t+s} - P_{I,t+s} I_{t+s}}{P_{t+s}} \right\} \tag{34}$$

Subject to the law of motion of home aggregate physical capital:

$$K_{t+1} = (1-\delta) K_t + I_t - \frac{\kappa}{2} \left(K_{t+1} - K_t \right)^2 \tag{35}$$

where δ is the depreciation rate, $\frac{\kappa}{2}\left(K_{t+1} - K_t\right)^2$ is the adjustment cost function, and $\kappa > 0$.

3.2.4 Government

The government liabilities consist of both outstanding public debt and money, while the only government asset is its share in the oil sector. The government consumes only domestically produced goods according to the following expenditure function:

$$G_t = \left[G_{t-1} \right]^{\rho_G} \left[G_0 \right]^{1-\rho_G} e^{\varepsilon_{G,t}} \tag{36}$$

where G_t is the total government expenditure in period *t*, ρ_G is the persistence parameter, and $\varepsilon_{G,t} \sim N(0, \sigma_{y_s}^2)$ represents a stochastic shock to the government expenditure. The government budget constraint is:

$$P_{H,t} G_t = P_{S,t} Y_{S,t} + T_t$$

With regard to the monetary policy, since the GCC currencies have de facto peg with the U.S. dollars, then the goal of the monetary policy is to keep the exchange rate constant up to an exogenous policy shock[27]:

$$e_t = e \xi_t \tag{37}$$

[27] The interest rate is the monetary policy instrument used by the GCC central bank.

where ξ_t is the exogenous policy shock with unitary mean. The log-linearized equation of the monetary policy equation can be written as[28]:

$$\tilde{i}_{H,t} = \tilde{i}^*_{F,t} + E_t \tilde{\xi}^{\varepsilon}_{t+1} \tag{38}$$

Equation (38) implies that the domestic interest rate moves one-to-one with the foreign interest rate and by an exogenous policy shock.

3.2.5 Foreign Sector

The home-currency price of oil is given by:

$$P_{S,t} = e_t P^*_{S,t} \tag{39}$$

The real price of oil in the foreign country is given by:

$$P^*_{r_s,t} = \frac{P^*_{S,t}}{P^*_t} \tag{40}$$

where P^*_t is the foreign price index of a representative bundle. From (40), we can define the real exchange rate between home and foreign country as:

$$RER_t = \frac{e_t P^*_t}{P_t} \tag{41}$$

3.2.6 Goods Market Clearing and Equilibrium

Each intermediate producing firm must meet the demand of its variety at the current price; that is:

$$Y_{H,t}(z_H) = \left(\frac{P_{H,t}}{P_{H,t}(z_H)} \right)^{\varepsilon_H} Y_{H,t} \tag{42}$$

where $Y_{H,t}$ is given by:

$$Y_{H,t} = C_{H,t} + I_{H,t} + G_t \tag{43}$$

[28] See appendix A for the derivation steps.

Using the budget constraint of households and the equilibrium conditions in the goods market, we can express the law of motion of the net foreign asset position of home economy as:

$$\frac{e_t B_{F,t}}{(1+i_{F,t})\Theta} - e_{t-1} B_{F,t-1} = P_{X,t} X_t - P_{M,t} M_t \tag{44}$$

where $P_{X,t}X_t = P_{S,t}Y_{S,t}$ is nominal exports, $P_{M,t}M_t = P_{F,t}Y_{F,t}$ is nominal imports.

Finally, the nominal GDP can be written as:

$$P_{Y,t}Y_t = P_t C_{H,t} + P_{I,t} I_{H,t} + P_{H,t} G_t + P_{X,t} X_t - P_{M,t} M_t \tag{45}$$

3.3 Simulation and Dynamic of the Model

In order to find the law of motion of each variable of the model presented in section 3.2, we need to determine both the values of the parameters and the steady state values of each variable. After choosing the previous values, we can apply any numerical technique to solve the log-linearized version of the model, presented in appendix A, in order to obtain the impulse response functions. In this chapter, I applied the algorithm proposed by Uhlig (1999) with QZ decomposition [29].

Since this is the first DSGE model to be built for the GCC area, many of the parameters of the model are unknowns due to the lack of data availability. For instance, there are no data on the share of imported consumption (investment) goods to total home consumption (investment). To overcome this problem, the model presented in section 3.2 is simplified in two aspects: first, I assume that the production function of the intermediate firms depends solely on labor in line with some of the previous literatures such as Gali and Monacelli (2002, 2005, 2007, and 2008), Clarida et al. (2001), and Vasicek and Musil (2006); second, I assume the absence of the importing sector in a similar way as Smets and Wouters (2003). The log-linearized version of the simplified model is presented on appendix B.

[29] The toolkit to solve the DSGE model can be found at: http://www2.wiwi.hu-berlin.de/wpol/html/toolkit.htm

The log-linearized model in appendix B was solved numerically in order to examine the dynamic impact of exogenous shocks on macroeconomic variables. In this section, I present the response of the GCC area economy to various shocks, namely the technology shock, the foreign interest rate shock (monetary shock), the government shock (fiscal shock), the oil price shock, and the oil supply shock.

Table 3.1 presents the utilized parameters to simulate the model. The subjective discount factor β is fixed at the value 0.99, which is consistent with steady state annualized real interest rate of 4%. The inverse intertemporal elasticity of substitution $1/\sigma_c$ in consumption is set to 1; thus, the utility function in consumption can be represented in logrithmetic form. For domestic intermediate firms who receive a signal to re- optimize their prices, the Calvo parameter ϕ_H is set to 0.75 as in Gali (2003), which means they will able to reset their prices once a year. The intertemporal elasticity of substitution among intermediate goods ε_H is set to 6, which implies a 20% markup on intermediate goods as applied by Curdia (2007) for emerging market. The risk premium on foreign bonds $\bar{\varpi}$ is set to 0.01. The persistence parameters $\rho_{Y_s}, \rho_{P_s^*}, \rho_G, \rho_A$ are chosen to be 0.95, 0.93, 0.95, 0.95, respectively. Since the currencies of the GCC economies are pegged to the U.S. dollar, the persistence parameter of U.S. interest rate ρ_{i_F} is set to 0.80 as estimated by Erceg *et. al* (2006).

Finally, using an annual data from 1970 to 2006 for the GCC area, I estimate the steady state values for the following ratios: the share of government consumption in GDP is set to 20%; the share of private consumption in GDP is 40%; the share of oil sector in GDP is 20%; and finally, oil revenue over government consumption is 2.5.

The impulse response functions of the simulated model are presented in figures 3.1 through 3.5. Figure 3.1 shows the impulse response function to the oil price shock. The shock to oil prices can be caused by various factors such as an increase in foreign demand especially from emerging markets, weather-driven demand, and speculative trading in commodities markets. The oil price shock increases the cost of production (i.e. real marginal cost) which implies a higher inflation rate. The effect of the oil price shock on the real GDP is positive. The transmission mechanism for the real GDP comes from the fact that the oil sector is owned by the government; therefore, the increase in oil revenues implies higher aggregate demands through the increase in government expenditures. The pro-cyclical and coincident behavior of oil prices with respect to real GDP is also supported by the econometric model (i.e. Generalized Dynamic Factor Model, GDFM) presented in chapter 2 (see Table 2.2). Since the GDFM summarizes the information contained in the panel of data, the DSGE model presented in this chapter enriches our understanding of the data.

Figure 3.2 shows the effect of an oil production shock. It represents a one-time 1% increase in oil production. An oil production shock can be caused by the same factors as an oil price shock, as well as technological progress in methods of extracting oil. The impulse response functions of inflation rate and real GDP show a positive response to an oil production shock. Since the oil sector in the GCC area represents on average 75% to 90% of total exports and 60% to 90% of government expenditures, the increase in oil production results in higher exports and government spending, which implies higher output. The pro-cyclical and coincident behavior of oil production indicators with respect to real GDP is also supported by the econometric model (Table 2.2, chapter 2). Moreover, the increase in aggregate demands due to higher government spending results in higher in inflationary pressure. Due to the assumption of price rigidities, a high inflation rate persists for two years before it starts converging to steady state.

Figure 3.3 shows the effect of a one-time positive technology shock. As predicted by the Real Business Cycle (RBC) literature, the inflation rate initially falls as the technology shock induces a reduction in the production costs, which translates into lower prices of final consumption goods. It is only after 18 months that the inflation rate starts moving to its steady state position. Also, since the technology shock reduces the marginal costs, it enables producers to increase production.

Therefore, the real GDP reacts positively to the technology shock. The initial effect on the real GDP lasts longer than the inflation rate.

Figure 3.4 shows the effect of a contractionary monetary policy. It represents a one-time 1% increase in interest rate. Both the inflation rate and real GDP decrease. The initial effect on inflation rate is slightly larger than the effect on output due to the fact that prices adjust to economic news faster than the change in the output production process. Since the model incorporates the price stickiness assumption, the inflation rate converges to steady state at a later time than the real GDP.

Figure 3.5 shows the effect of an expansionary fiscal spending shock. Both the inflation rate and the real GDP respond positively to the government spending shock. The transmission mechanism of the shock works through government expenditures. Since the oil sector is owned by the government, higher government revenues lead to higher domestic demand by government, which creates inflationary pressure. Also, it leads to higher output through the increase in government spending. Both variables persist for four to five years before they start converging to their steady state values. These results are consistent with the traditional macroeconomic model such as the IS-LM model (Abel and Bernanke 2005) and the RBC model with Ricardian households and price stickiness.

3.4 Conclusion

In this chapter, I layout a structural small open DSGE model with a fixed exchange rate regime for the GCC area. The model is simulated to examine the dynamic impact of exogenous shocks on macroeconomic variables.

The model belongs to the New Open Economy Macroeconomics (NOEM) approach, which provides a valuable tool for policy analysis since NOEM is a well-specified microeconomic foundation approach. In the model, there are households, firms (domestic firms, importing firms, oil sector), an investment and capital accumulation sector, a government represented by a fiscal authority and a central bank, and finally a foreign sector represented by foreign output, inflation, and interest rate. Moreover, the model includes some nominal rigidities and imperfect competition. Specifically, the model incorporates nominal and real rigidities such price stickiness, habit persistence in consumption, capital adjustment costs, and incomplete exchange rate pass-through. These frictions have been introduced by the New Keynesian theorists to account for the actual dynamic persistence of macroeconomic variables. Finally, in accordance with the common contemporary practices of most central banks, I model the monetary aggregates as endogenous variables and the short-term interest rate as the monetary policy instrument.

The log-linearized version of the model is simulated by utilizing the algorithm proposed by Uhlig (1999) with QZ decomposition. The behavior of macroeconomic variables are analyzed through the impulse response functions, since those functions offer a good approximation of macroeconomic variables behavior in response to exogenous shocks.

The main results of the model presented in this chapter can be summarized as follows. When there is a positive oil price shock, it results in a higher inflation rate due to the increase in production costs. The effect on real GDP is also positive due to higher aggregate demands coming from increased government spending. Similarly, a positive oil production shock implies a higher inflation rate and higher real GDP. While higher real GDP is caused by the increase in oil exports and government expenditures, a higher inflation rate is caused by the increase in aggregate demands due to higher government spending. Moreover, the effect of a contractionary monetary policy generates a negative response to inflation rate and real GDP, whereas the effect of an expansionary fiscal policy generates a positive response to both variables. Finally, a positive technology shock generates hump-shaped responses of inflation rate and real GDP due to the decrease in the production costs.

To the best of my knowledge, this is the first attempt to layout a DSGE model for the GCC area. The model captures essential features of the GCC area, mainly the dominance of the oil sector and the fixed exchange rate regime. The simulated model presented in this chapter is a step forward for understanding and analyzing the business cycle evolution of the GCC area. Once data become available in the future, the model can serve a “workhorse” by estimating or calibrating the model in order to extract historical shocks, obtain variance decomposition, and forecast key macroeconomic variables of interest.

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Table 3.1: Baseline Parameters and Steady State Values

Parameter		Steady state value
Subjective discount value	β	.99
Relative risk aversion	σ_c	1
Calvo probability	ϕ_H	.75
Price elasticity of demand	ε_H	6
Risk premium	$\bar{\omega}$	.01
AR (1) of oil production	ρ_{Y_s}	.95
AR (1) of oil price	$\rho_{P_s^*}$	.93
AR (1) of government expenditures	ρ_G	.95
AR (1) of technology	ρ_A	.95
AR (1) of foreign interest rate	ρ_{i_F}	.8
Share of government consumption in GDP		.2
Share of private consumption in GDP		.4
Share of oil sector in GDP		.4
Oil revenue over government consumption		2.5

Figure 3.1: Impulse Response Functions to an Oil Price Shock

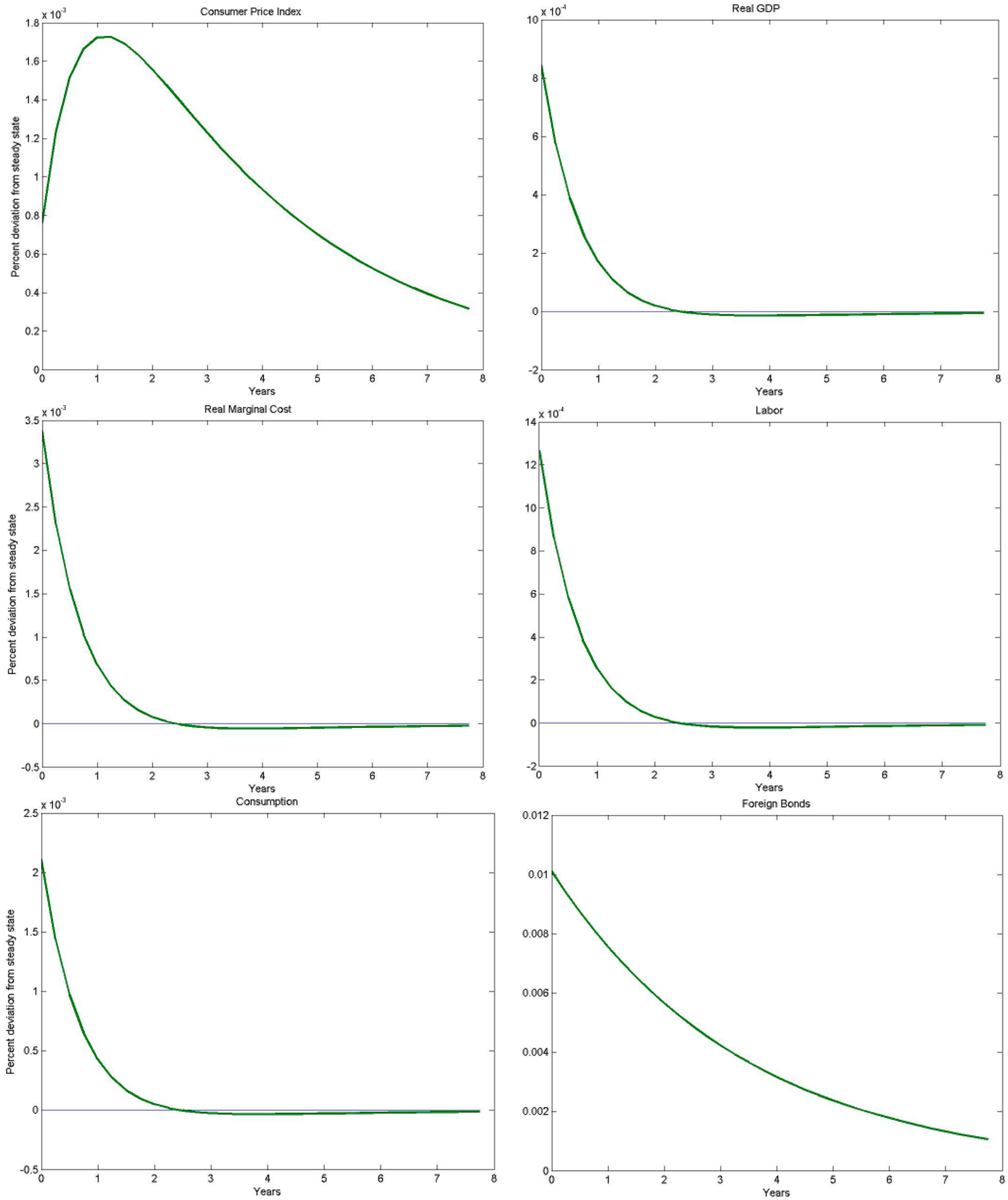


Figure 3.2: Impulse Response Functions to an Oil Production Shock

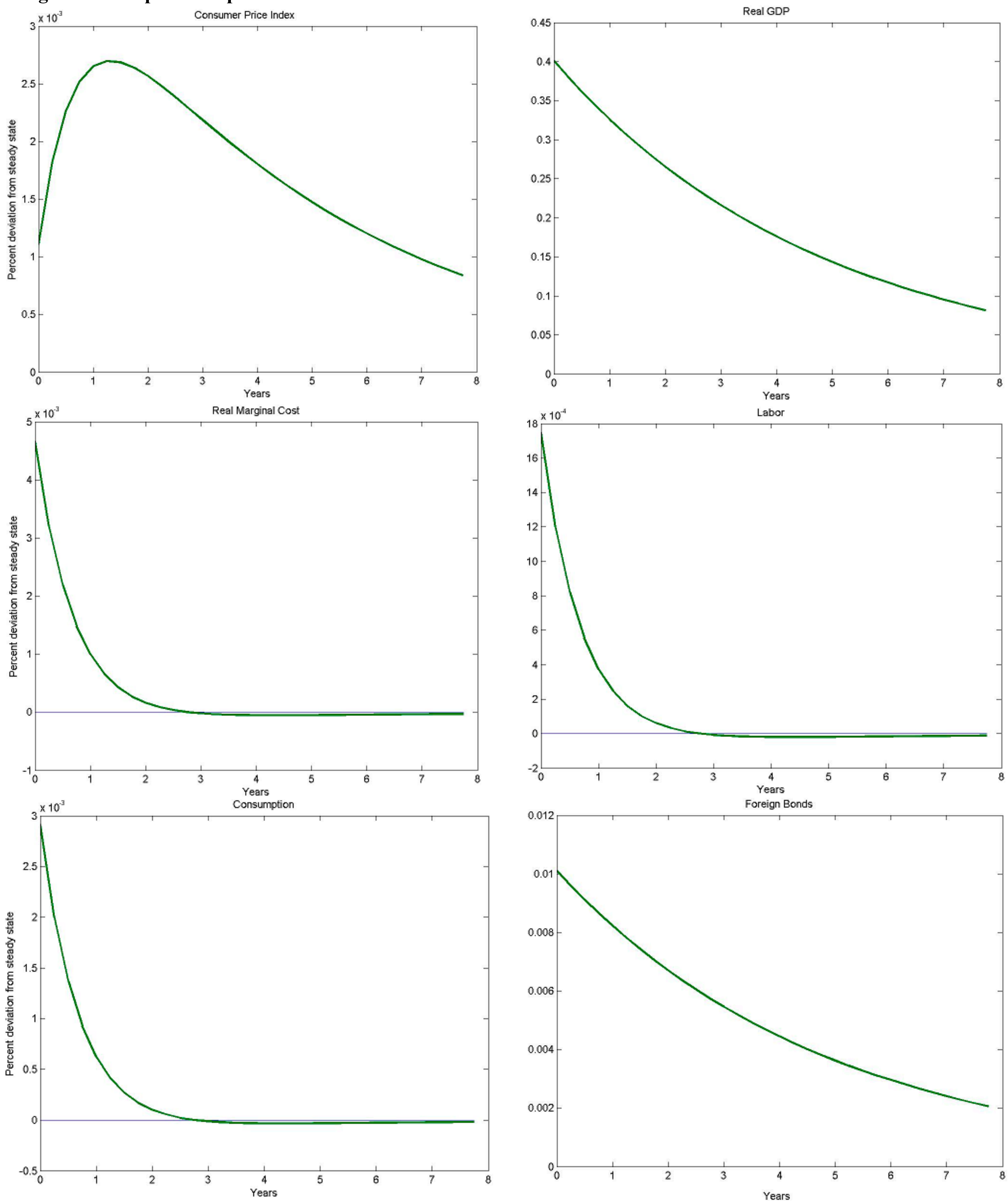


Figure 3.3: Impulse Response Functions to a Technology Shock

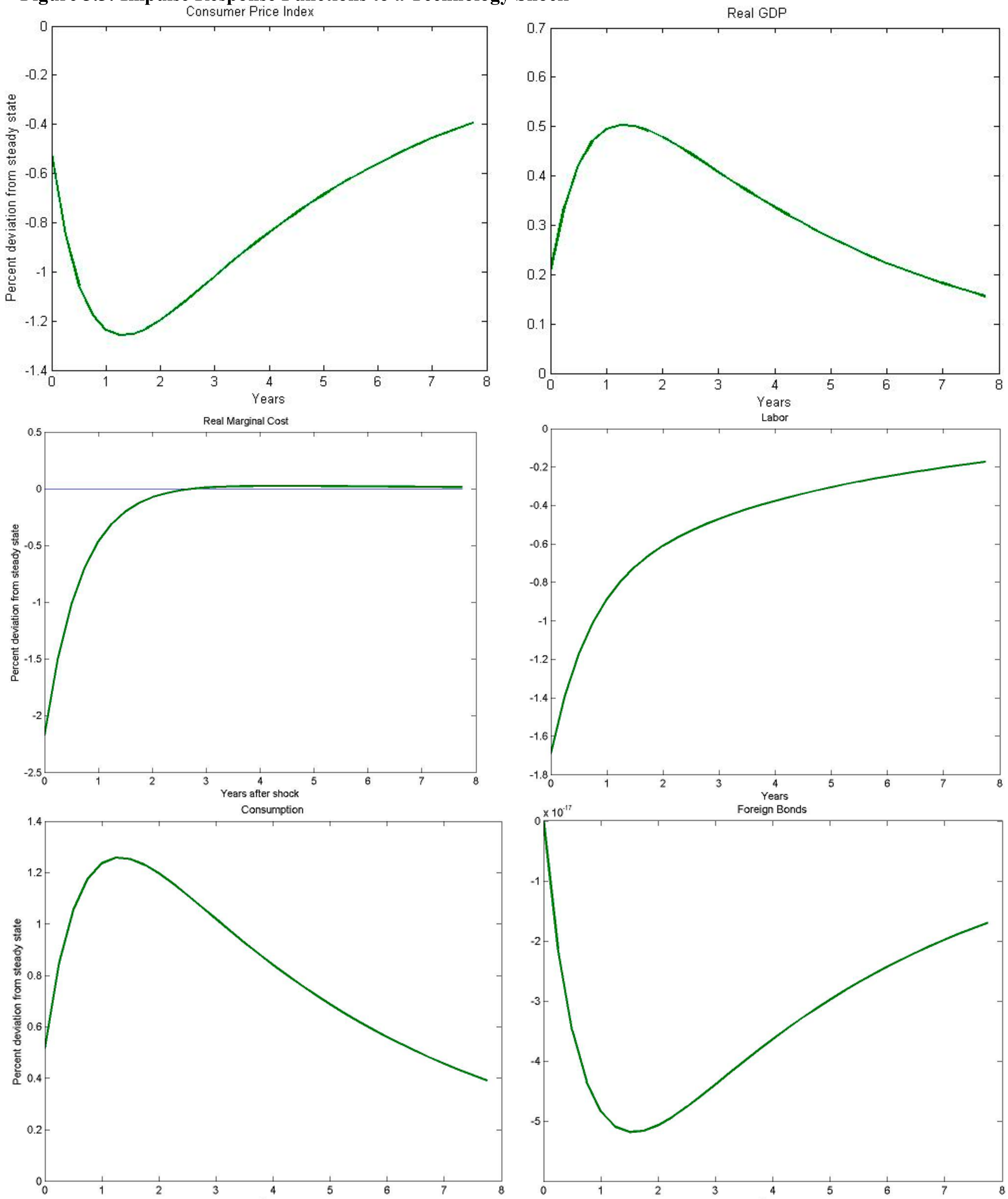


Figure 3.4: Impulse Response Functions to a Monetary Policy Shock

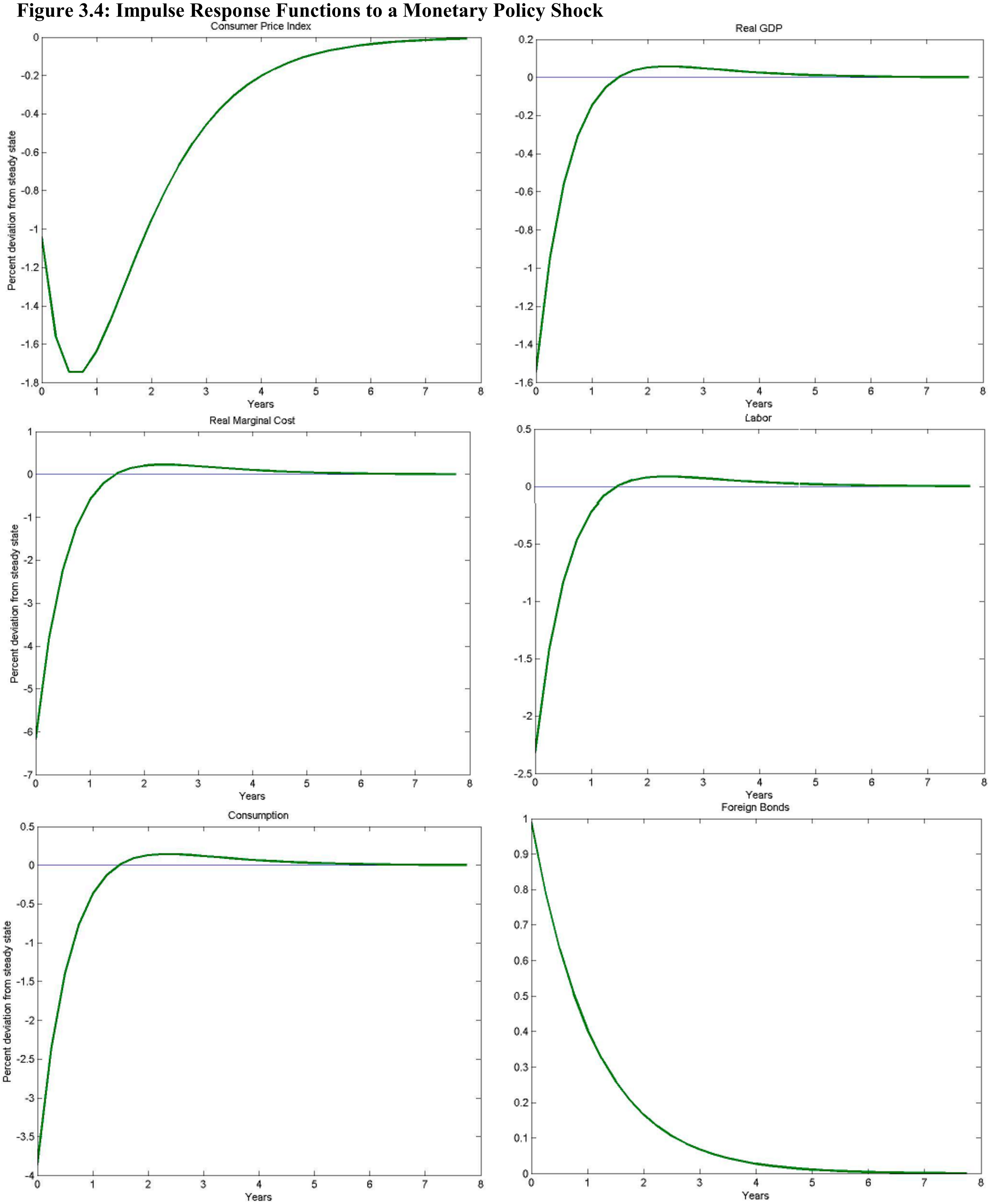
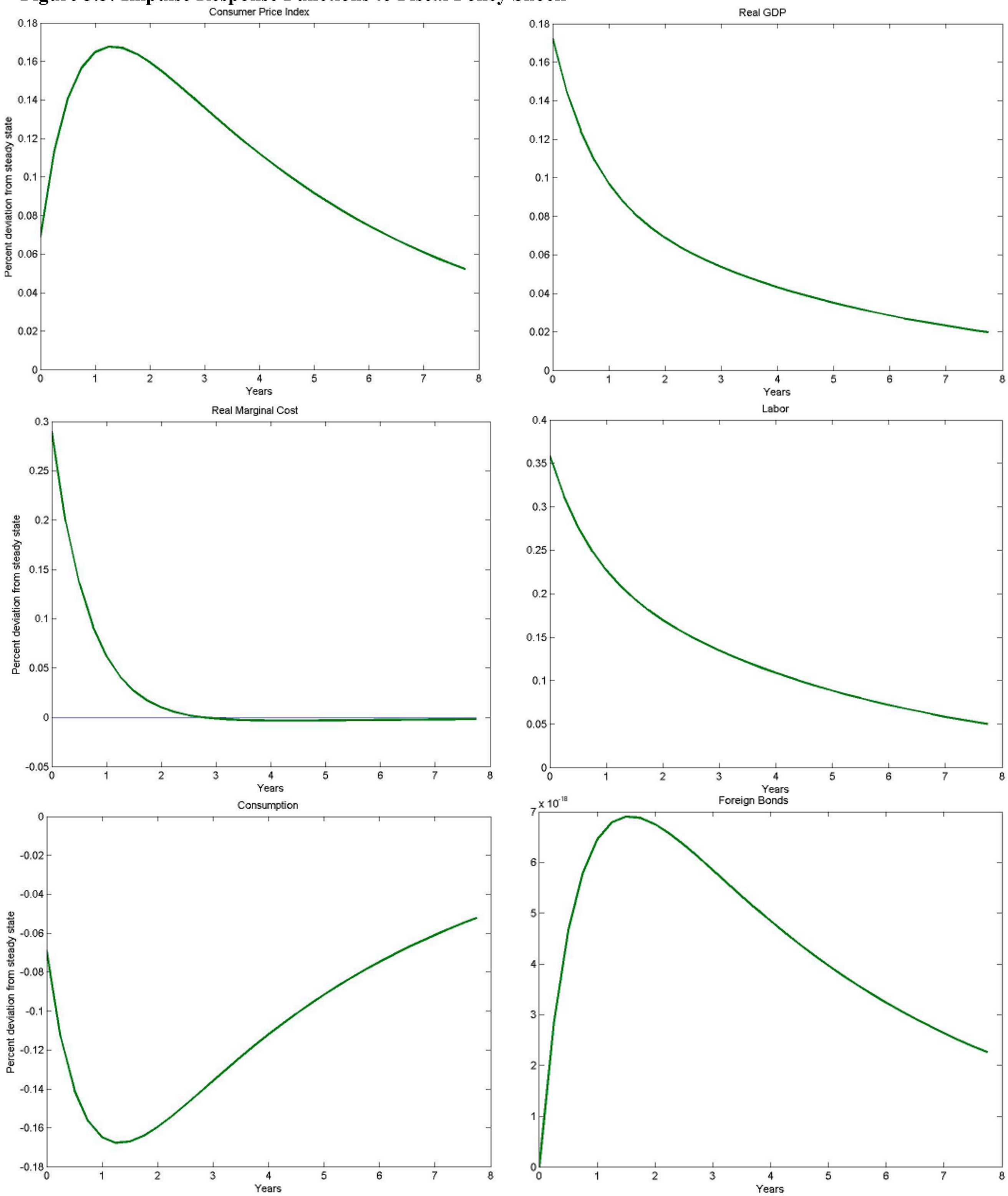


Figure 3.5: Impulse Response Functions to Fiscal Policy Shock



Appendix A Log-linear Version of the Model

- **Consumption goods bundle**

$$\tilde{C}_{H,t} = \eta_c \left(\tilde{P}_t - \tilde{P}_{H,t} \right) + \tilde{C}_t$$
$$\tilde{C}_{F,t} = \eta_c \left(\tilde{P}_t - \tilde{P}_{F,t} \right) + \tilde{C}_t \tag{2.1}$$

- **The aggregate consumption**

$$\beta E_t \left\{ (1+i_{H,t}) \frac{\xi_{t+1}^c}{\xi_t^c} \left(\frac{C_t - hC_{t-1}}{C_{t+1} - hC_t} \right) \frac{P_t}{P_{t+1}} \right\} = 1 \tag{2.2}$$

In steady state, (2.2) can be written as:

$$\beta(1+\bar{i}_H) = 1$$

Multiplying out the denominator of (2.2) yields:

$$\beta E_t \left\{ (1+i_{H,t}) \xi_{t+1}^c \left(C_t - hC_{t-1} \right) P_t \right\} = E_t \left\{ \xi_t^c \left(C_{t+1} - hC_t \right) P_{t+1} \right\} \tag{2.3}$$

Log-linearize both sides of (2.3) to obtain:

$$\tilde{C}_t \approx \frac{\tilde{C}_{t+1}}{1+h} + \frac{h\tilde{C}_{t-1}}{1+h} - \frac{1-h}{1+h}(\tilde{i}_{H,t} - \tilde{\pi}_{t+1}^C) + \frac{1-h}{1+h}\tilde{\zeta}_t^C - \frac{1-h}{1+h}(E_t \tilde{\zeta}_{t+1}^C) \tag{2.4}$$

- **The final goods pricing rule**

$$P_{H,t} = \left[\int_0^1 P_{H,t}(z_H)^{1-\varepsilon_H} dz_H \right]^{\frac{1}{1-\varepsilon_H}}$$

which can be written as:

$$P_{H,t}^{1-\varepsilon_H} = \phi_H P_{H,t-1}^{1-\varepsilon_H} + (1-\phi_H) P_{H,t}^{*1-\varepsilon_H} \tag{2.5}$$

In steady state, the final goods price and the intermediate goods price are the same:

$$\bar{P}_H = \bar{P}_H^* = \bar{P}_H^*(z_H)$$

Log-linearize both sides of (2.5) to obtain:

$$\tilde{P}_{H,t} \approx \phi_H \tilde{P}_{H,t} + (1-\phi_H)\tilde{P}_{H,t}^*(z_H) \tag{2.6}$$

- **The domestic intermediate goods pricing rule**[30]

$$P_{H,t}^*(z_H) = \frac{\varepsilon_H}{\varepsilon_H - 1} \frac{E_t \sum_{i=0}^{\infty} (\beta\phi_H)^i P_{H,t+i} Y_{H,t+i}(z_H) \frac{W_{t+i}}{(1-\alpha)A_{H,t+i}} \left(\frac{(1-\alpha)R_{t+i}}{\alpha\, W_{t+i}} \right)^{\alpha}}{E_t \sum_{i=0}^{\infty} (\beta\phi_H)^i Y_{H,t+i}(z_H)} \tag{2.7}$$

In the steady state, we have:

[30] I followed the procedure proposed by McCandless (2008).

$$\frac{\varepsilon_H}{\varepsilon_H - 1} = \frac{1}{\dfrac{W_{t+i}}{(1-\alpha)A_{H,t+i}}\left(\dfrac{(1-\alpha)R_{t+i}}{\alpha\; W_{t+i}}\right)^{\alpha}}$$

Multiply both sides of (2.7) by the denominator gives:

$$E_t\sum_{i=0}^{\infty}(\beta\phi_H)^i P^*_{H,t}(z_H)Y_{H,t+i}(z_H) = \frac{\varepsilon_H}{\varepsilon_H - 1}E_t\sum_{i=0}^{\infty}(\beta\phi_H)^i P_{H,t+i}Y_{H,t+i}(z_H)$$

$$\times\; \frac{W_{t+i}}{(1-\alpha)A_{H,t+i}}\left(\frac{(1-\alpha)R_{t+i}}{\alpha\; W_{t+i}}\right)^{\alpha} \qquad (2.8)$$

Log-linearization of the left hand side is given by:

$$\frac{\overline{P}^*_H(z_H)\overline{Y}_H(z_H)}{1-\beta\phi_H}\left(1+\tilde{P}^*_{H,t}(z_H)\right) + \overline{P}^*_H(z_H)\overline{Y}_H(z_H)E_t\sum_{i=0}^{\infty}(\beta\phi_H)^i\tilde{Y}_{H,t+i}(z_H) \qquad (2.9)$$

Log-linearization of the right hand side is given by:

$$\overline{P}^*_H(z_H)\overline{Y}_H(z_H)E_t\sum_{i=0}^{\infty}(\beta\phi_H)^i\left[1+\tilde{P}^*_{H,t+i}+\tilde{Y}_{H,t+i}(z_H)+(1-\alpha)\tilde{W}_{t+i}+\alpha\tilde{R}_{t+i}-\tilde{A}_{H,t+i}\right] \qquad (2.10)$$

combine (1.9) and (1.10) to obtain:

$$\tilde{P}^*_{H,t}(z_H) = \left(1-\beta\phi_H\right)E_t\sum_{i=0}^{\infty}(\beta\phi_H)^i\left[\tilde{P}^*_{H,t+i}+(1-\alpha)\tilde{W}_{t+i}+\alpha\tilde{R}_{t+i}-\tilde{A}_{H,t+i}\right] \qquad (2.11)$$

- **The New Keynesian domestic Phillips curve**
  substitute (2.11) in (2.6) to obtain

$$\tilde{P}_{H,t} \approx \phi_H\tilde{P}_{H,t-1} + (1-\phi_H)\left(1-\beta\phi_H\right)E_t\sum_{i=0}^{\infty}(\beta\phi_H)^i\left[\tilde{P}^*_{H,t+i}+(1-\alpha)\tilde{W}_{t+i}+\alpha\tilde{R}_{t+i}-\tilde{A}_{H,t+i}\right]$$

(2.12)

applying quasi differencing, multiplying by $\left(1-\beta\phi_H L^{-1}\right)$, to the left hand side of (2.12) gives:

$$\tilde{P}_{H,t} - \beta\phi_H E_t\tilde{P}_{H,t+1} \qquad (2.13)$$

applying quasi differencing to the right hand side f (2.12) yields:

$$\begin{aligned}
&\phi_H\tilde{P}_{H,t-1} - \beta\phi_H\phi_H\tilde{P}_{H,t} + \left(1-\phi_H\right)\left(1-\beta\phi_H\right)\\
&\times E_t\sum_{i=0}^{\infty}(\beta\phi_H)^i\left[\tilde{P}^*_{H,t+i}+(1-\alpha)\tilde{W}_{t+i}+\alpha\tilde{R}_{t+i}-\tilde{A}_{H,t+i}\right]\\
&+\beta\phi_H\left(1-\phi_H\right)\left(1-\beta\phi_H\right)\\
&\times E_t\sum_{i=0}^{\infty}(\beta\phi_H)^i\left[\tilde{P}^*_{H,t+1+i}+(1-\alpha)\tilde{W}_{t+1+i}+\alpha\tilde{R}_{t+1+i}-\tilde{A}_{H,t+1+i}\right]
\end{aligned} \qquad (2.14)$$

Since most terms of (2.14) are cancelled out, we left with:

$$\phi_H \tilde{P}_{H,t-1} - \beta\phi_H\phi_H \tilde{P}_{H,t} + (1-\phi_H)(1-\beta\phi_H)$$
$$\times E_t \sum_{i=0}^{\infty} (\beta\phi_H)^i \left[\tilde{P}^*_{H,t} + (1-\alpha)\tilde{W}_t + \alpha\tilde{R}_t - \tilde{A}_{H,t} \right]$$

To obtain the Phillips curve, we combine (2.13) and (2.4):

$$\left[\tilde{P}_{H,t} - \tilde{P}_{H,t-1}\right] = \beta\left[E_t\tilde{P}_{H,t+1} - \tilde{P}_{H,t}\right] + \frac{(1-\phi_H)(1-\beta\phi_H)}{\phi_H}\left[(1-\alpha)\tilde{W}_t + \alpha\tilde{R}_t - \tilde{A}_{H,t}\right] \tag{2.15}$$

or as commonly stated in the literatures:

$$\ln \pi_{H,t} = \beta E_t \ln \pi_{H,t+1} + \frac{(1-\phi_H)(1-\beta\phi_H)}{\phi_H}\widetilde{RMC_t} \tag{2.16}$$

- **The New Keynesian foreign Phillips curve**

Following the same steps as in the domestic Phillips curve, the foreign Phillips curve is given by:

$$\left[\tilde{P}_{F,t} - \tilde{P}_{F,t-1}\right] = \beta\left[E_t\tilde{P}_{F,t+1} - \tilde{P}_{F,t}\right] + \frac{(1-\phi_F)(1-\beta\phi_F)}{\phi_F}\left[(1-\alpha)\tilde{W}_t + \alpha\tilde{R}_t - \tilde{A}_{F,t}\right] \tag{2.17}$$

- **The New Keynesian overall Phillips Curve**

$$P_t = \left[\gamma_c (P_{H,t})^{1-\eta_c} + (1-\gamma_c)(P_{F,t})^{1-\eta_c}\right]^{\frac{1}{1-\eta_c}}$$

or as:

$$\left[\frac{P_t}{P_{H,t}}\right]^{1-\eta_c} = \gamma_c + (1-\gamma_c)\left[\frac{P_{F,t}}{P_{H,t}}\right]^{1-\eta_c} \tag{2.18}$$

Log-linearization of (2.18) gives:

$$\tilde{P}_t = \gamma_c\tilde{P}_{H,t} + (1-\gamma_c)\tilde{P}_{F,t} \tag{2.19}$$

Therefore, the overall Phillips curve can be written as:

$$\ln \pi_t = \gamma_c \ln \pi_{H,t} + (1-\gamma_c)\ln \pi_{F,t} \tag{2.20}$$

- **The oil sector production**

$$\tilde{Y}_{S,t} = \rho_{y_s}\tilde{Y}_{S,t-1} + (1-\rho_{y_s})\tilde{Y}_{S,0} + \tilde{\varepsilon}_{ys,t} \tag{2.21}$$

- **Investment and capital accumulation**

$$\tilde{K}_{t+1} = (1-\delta)\tilde{K}_t + \delta\tilde{I}_t \tag{2.22}$$

$$\tilde{I}_{H,t} = \eta_I \left(\tilde{P}_{I,t} - \tilde{P}_{H,t} \right) + \tilde{I}_t$$
$$\tilde{I}_{F,t} = \eta_I \left(\tilde{P}_{I,t} - \tilde{P}_{F,t} \right) + \tilde{I}_t \qquad (2.23)$$
$$\tilde{P}_{I,t} = \gamma_I \tilde{P}_{H,t} + \left(1-\gamma_I\right) \tilde{P}_{F,t}$$

- **The fiscal policy**

$$\tilde{G}_t = \rho_{y_s} \tilde{G}_{t-1} + \left(1-\rho_g\right) \tilde{G}_0 + \tilde{\varepsilon}_{g,t} \qquad (2.24)$$

The log-linearized version of the real government budget constraint is given by:

$$0 = \tilde{G}_t - \frac{\overline{P}_s^* \overline{Y}_s}{\overline{P}\overline{G}} \left(\tilde{P}_{s,t}^* - \tilde{P}_t + \tilde{Y}_s \right) + \frac{\overline{T}}{\overline{P}\overline{G}} \left(\tilde{T}_t - \tilde{P}_t \right) \qquad (2.25)$$

- **Monetary policy rule**

$$\left(1+i_t\right) = \left(1+i_{F,t}\right) \Theta E_t \left\{ \frac{e_{t+1}}{e_t} \right\} \qquad (2.26)$$

The steady state of (2.26) is given by

$$\left(1+\overline{i}_H\right) = \left(1+\overline{i}_F\right)\Theta$$

Log-linearization of (2.26) gives:

$$\tilde{i}_{H,t} = \tilde{i}_{F,t} + E_t \Delta e_{t+1}$$

or as

$$\tilde{i}_{H,t} = \tilde{i}_{F,t} + E_t \tilde{\xi}_{t+1}^{\varepsilon} \qquad (2.27)$$

- **The foreign sector**

The real price of oil is given by:

$$\frac{P_{S,t}}{P_t} = \frac{e_t P_{S,t}^*}{P_t}$$

Since the real exchange rate is given by:

$$RER_t = \frac{e_t P_t^*}{P_t}$$

Then,

$$\frac{P_{S,t}}{P_t} = RER_t \frac{P_{S,t}^*}{P_t^*} \qquad (2.28)$$

Log-linearize (2.28) to obtain:

$$\tilde{P}_{S,t} - \tilde{P}_t = \widetilde{RER}_t + \left(\tilde{P}_{S,t}^* - \tilde{P}_t \right) \qquad (2.29)$$

- **The market clearing conditions**
  - The total demand of domestic goods

$$Y_{H,t} = C_{H,t} + I_{H,t} + G_t \qquad (2.30)$$

Log-linearization of (2.30) gives:

$$\tilde{Y}_{H,t} = \frac{\bar{C}_H}{\bar{Y}_H}\tilde{C}_{H,t} + \frac{\bar{I}_H}{\bar{Y}_H}\tilde{I}_{H,t} + \frac{\bar{G}}{\bar{Y}_H}\tilde{G}_t \tag{2.31}$$

- The total supply of domestic goods

$$\tilde{Y}_{H,t} = \tilde{A}_t + \alpha\tilde{K}_t + (1-\alpha)\tilde{l}_t \tag{2.32}$$

- The foreign assets position

$$\begin{aligned}\left(\bar{e}\bar{B}_F\right)\beta\tilde{B}_{F,t} &= \left(\bar{e}\bar{B}_F\right)\left[\beta\tilde{i}_{F,t} - \left(\beta\tilde{e}_t - \tilde{e}_{t-1}\right) + \tilde{B}_{F,t-1}\right] \\ &\quad + \bar{P}_X\bar{X}\left(\tilde{P}_{X,t} + \tilde{X}_t\right) - \bar{P}_M\bar{M}\left(\tilde{P}_{M,t} + \tilde{M}_t\right)\end{aligned} \tag{2.33}$$

- The real GDP

$$P_{Y,t}Y_t = P_tC_t + P_{I,t}I_t + P_{H,t}G_t + P_{X,t}X_t - P_{M,t}M_t \tag{2.34}$$

The steady state of (2.34) is given by:

$$\bar{P}_Y\bar{Y} = \bar{P}\bar{C} + \bar{P}_I\bar{I} + \bar{P}_H\bar{G} + \bar{P}_X\bar{X} - \bar{P}_M\bar{M}$$

Log-linearize (1.34) to obtain:

$$\tilde{Y}_t = \frac{\bar{P}\bar{C}}{\bar{P}_Y\bar{Y}}\tilde{C}_t + \frac{\bar{P}_I\bar{I}}{\bar{P}_Y\bar{Y}}\tilde{I}_t + \frac{\bar{P}_H\bar{G}}{\bar{P}_Y\bar{Y}}\tilde{G}_t + \frac{\bar{P}_X\bar{X}}{\bar{P}_Y\bar{Y}}\tilde{X}_t - \frac{\bar{P}_M\bar{M}}{\bar{P}_Y\bar{Y}}\tilde{M}_t \tag{2.35}$$

where

$$\tilde{X}_t = \frac{\bar{Y}_s}{\bar{X}}\tilde{Y}_{s,t}$$

$$\tilde{M}_t = \frac{\bar{C}_F}{\bar{M}}\tilde{C}_{F,t} + \frac{\bar{I}_F}{\bar{M}}\tilde{I}_{F,t}$$

Appendix B Log-linear Version of the Simulated Model

- The home production function

$$0 = \tilde{Y}_H - \tilde{A}_t - \tilde{l}_t$$

- The real marginal cost

$$0 = \widetilde{rmc}_t - \tilde{Y}_H - \tilde{C}_t + 2\tilde{A}_t$$

- The government budget constraint

$$0 = \tilde{G}_t - \frac{\overline{P}_s^* \overline{Y}_s}{\overline{P}\overline{G}}\left(\tilde{P}_{s,t}^* - \tilde{P}_t + \tilde{Y}_s\right) + \frac{\overline{T}}{\overline{P}\overline{G}}\left(\tilde{T}_t - \tilde{P}_t\right)$$

- The monetary policy rule

$$0 = \tilde{i}_{H,t} - \tilde{i}_{F,t} + \varpi \overline{B}_F \tilde{B}_{F,t}$$

- The household budget constraint

$$0 = \overline{C}\tilde{C}_t + \frac{\overline{M}}{\overline{P}}\tilde{M}_t + \frac{\beta \overline{B}_F}{\overline{P}}\left[\tilde{B}_{F,t} - \tilde{i}_{F,t} + \varpi \tilde{B}_{F,t}\right] - \frac{\overline{M}}{\overline{P}}\tilde{M}_{t-1}$$
$$-\overline{Wl}\tilde{W}_t - \overline{Wl}\tilde{l}_t - \frac{\overline{B}_F}{\overline{P}}\tilde{B}_{F,t-1} - \frac{\overline{T}}{\overline{P}}\tilde{T}_t + \left[\frac{\overline{B}_F}{\overline{P}} + \frac{\overline{T}}{\overline{P}} - \frac{\beta}{\overline{P}}\right]\tilde{P}_t$$

- The foreign net asset position

$$0 = \beta \overline{B}_F \tilde{B}_{F,t} - \overline{B}_F\left[\beta\left(\tilde{i}_{F,t} - \varpi \tilde{B}_{F,t}\right) + \tilde{B}_{F,t-1}\right] - \overline{P}_s^* \overline{Y}_s \tilde{P}_{s,t}^* - \overline{P}_s^* \overline{Y}_s \tilde{Y}_{s,t}$$

- The market clearing condition for domestic goods

$$0 = \tilde{Y}_{H,t} - \frac{\overline{C}}{\overline{Y}_H}\tilde{C}_t - \frac{\overline{G}}{\overline{Y}_H}\tilde{G}_t$$

- The real GDP

$$0 = \frac{\overline{P}\overline{C}}{\overline{P}_Y \overline{Y}}\tilde{C}_t + \frac{\overline{P}\overline{G}}{\overline{P}_Y \overline{Y}}\tilde{G}_t + \frac{\overline{P}_s \overline{Y}_s}{\overline{P}_Y \overline{Y}}\tilde{Y}_s - \tilde{Y}_t$$

- The consumption Euler equation

$$0 = E_t \tilde{C}_{t+1} - \tilde{C}_t - \tilde{i}_{H,t} + E_t \tilde{P}_{t+1} - \tilde{P}_t$$

- The New Keynesian Phillips Curve

$$0 = \beta\left[E_t \tilde{P}_{t+1} - \tilde{P}_t\right] - \left[\tilde{P}_t - \tilde{P}_{t-1}\right] + \frac{(1-\phi)(1-\beta\phi)}{\phi}\left[\widetilde{rmc}\right]$$

Chapter 4: Forecasting GDP and Inflation for the GCC Area in a "Data-Rich Environment"

4.1 Introduction

Many economic decisions, whether they are made by economists at central banks, fiscal policymakers, private firms, or consumers, are based to some extent on forecasts of relevant macroeconomic variables such as real output, consumption, investment, unemployment, interest rates, and inflation. Policymakers at the government level use those forecasts to conduct monetary and fiscal policy, while other economic agents use those forecasts to make sound economic decisions. Thus, the need for producing accurate forecasts of the key macroeconomic variables has become crucial for both policymakers and economic agents. In order to forecast any macroeconomic variable, it is sufficient to fit a small-scale time series model such as an AutoRegressive model (AR), or a Vector AutoRegressive (VAR) model. Although those models include only a small number of variables, they usually produce good short-term forecasts. However, in a "rich-data environment," where information is scattered over a large number of economic time series, policymakers and private forecasting firms have been able to exploit the information contained in a large panel of data in order to forecast any macroeconomic variable of interest.

However, it is not often feasible to estimate the forecasting equation of any target variable with all relevant variables. Under such constraints, a set of econometric models, such as factor models, can allow the exploitation of the information contained in a large dataset while keeping the dimension of the forecasting equation small. With the creation of the monetary union in the Gulf Cooperation Council (GCC) area, policymakers at the prospective supernational monetary agency will focus on forecasting key macroeconomic variables of interest such as real GDP, inflation, unemployment etc. Central bankers will have to scrutinize hundreds of economic indicators both at the national and regional level when making these forecasts. They will be more interested in examining common shocks that drive the GCC economies rather than a country-specific shock. Therefore, from a policy point of view, using a factor model can be a good analytical and empirical tool for policymakers since the estimated common shocks can be exploited to forecast key macroeconomic variables of interest.

Factor models have been widely accepted in academic work and in research conducted by various reputable institutions such as Federal Reserve Bank of Chicago and Center for Economic Policy Research (CEPR)[31]. With the increase in the quality and quantity of data both at the aggregate and disaggregate level, econometricians have consequently developed more statistically oriented models such as factor models, which summarize the information contained in large panels of time series as a few common factors "or shocks"[32]. Those factors can then be used as predictors to forecast any key macroeconomic variable of interest. In the seminal works of Stock and Watson (2002a, b) and Forni *et. al*. (2000, 2005), they found substantially smaller mean squared errors from factor models forecasts than from small-scale time series models.

The underlying purpose of factor models is to summarize the information contained in a large cross-section of time series by a few common shocks. That is, we can represent the movement of any time series as the sum of two mutually orthogonal unobservable components: a *common component* and an *idiosyncratic component.* The common component is a linear combination of the common shocks, and therefore it is strongly correlated with the rest of the panel. By contrast, the idiosyncratic component is a variable specific shock and it is weakly correlated across the panel. Since those two components are unobservable, they have to be estimated.

There are two important methods in the literature to estimate unobservable components in factor models. In the time domain, Stock and Watson (2002a)

[31] The Federal Reserve Bank of Chicago's Activity Index (CFNAI) is based on the static factor model as proposed by Stock and Watson, while the Center for Economic Policy Research (CEPR) coincident indicator is based on the dynamic factor model as proposed by Forni *et al.* (2000).
[32] Stock and Watson (2006) provide a thorough survey of all factor models which exploit the information contained in a large panel in order to forecast any target variable of interest.

introduced dynamics into the approximate factor model (from hereafter, it is referred to as Static Factor Model, SFM) and used a static principal components method to estimate common components. Alternatively, in the frequency domain, Forni *et al.* (2000, 2004, and 2005) introduced the Generalized Dynamic Factor Model (GDFM) and utilized a dynamic principal components procedure to estimate and to forecast common components[33]. In both models, there are two steps to obtain forecasts from any factor models. In the first step, by estimating the factor models, the dimension of a large panel of data is reduced to a few common factors by exploiting the covariation across economic variables. In the second step, the estimated factors are then entered into the forecasting equation to predict the key macroeconomic variables of interest. In this chapter, I compare the forecast performance of the previous two methods for the real GDP growth rate and inflation rate of the GCC area.

The results conveyed in this chapter are distinguishable from the existing literatures in the following ways: first, to my knowledge, this is an original effort to generate short-term forecasts of key macroeconomic variables for the GCC economies, namely the real GDP growth rate and inflation rate, by utilizing both the GDFM and SFM; second, with the commencement of the monetary union in 2010, monetary policymakers at the prospective GCC central bank will have to scrutinize a large number of economic variables, both at the national and regional level, in order to conduct a sound monetary policy. Since GDFM and SFM synthesize information coming from different sources, the forecasting results of this chapter can be used as a tool to conduct a sound monetary policy at the GCC regional level. Furthermore, while there are some well-established and large databases for the U.S. and Euro areas, there is no single dataset containing macroeconomic time series for the GCC area. Therefore, macroeconomic variables are collected from different sources to construct

[33] Unlike the static principal components method, which is based on the eigenvalues decomposition of the contemporaneous covariance matrix, the dynamic principal components method relies on the spectral density matrix of the data wherein data are weighted and shifted across time (dynamic co-variations).

a dataset that covers a wide range of economic phenomena for the GCC area. The final database, which is quantitatively and temporally rich, can be a useful tool for future research on the GCC economies. Finally, while most of the previous literature has been applied to the Euro or Asian Pacific area, or to the United States, this chapter forecasts key macroeconomic variables of interest for the GCC area, which has been increasingly important in the global economy because of its abundant financial and natural resources. To test the efficiency gain of each method, I compared the forecast performance of those two methods over different forecasting horizons, as well as using different forecasting equations.

The remainder of this chapter is organized as follows: section 4.2 gives a brief summary of previous literatures that compared the forecasting performance of different factor models; section 4.3 gives an overview of SFM and GDFM; section 4.4 describes the procedures for constructing the GCC dataset; section 4.5 provides the empirical results; section 4.6 concludes.

4.2 Literature Review

Using a meta-analysis approach, Eickmeier and Ziegler (2006) assess the relative forecasting performance of different factor models, which exploit information in data-rich environments relative to small-scale time series models. The results of meta-analysis show the forecast performance of factor models outperforms small-scale models. In particular, forecasts of factor models for the U.S. output are better than the Euro-area, while there is no significant difference for inflation. The size of the dataset, frequency of observations, and rolling window forecasts deliver a better factor forecast performance, whereas a balanced or unbalanced dataset, multi-step direct or an iterated forecast, and pre-selecting some variables to be included in factor estimation do not seem to improve the performance of factor forecasts relative to other benchmark models.

In addition, Forni *et al.* (2005) provide theoretical arguments in favor of GDFM, which is based on the *generalized principal component method*, as opposed to the Stock and Watson (2002a) model, which is based on a static principal component approach. They also show that the forecasting performance of their predictors outperform Stock and Watson (2002a), both in simulations and in empirical exercises, using Stock and Watson's dataset. Boivin and Ng (2005) use simulation and empirical examples to compare the forecasting performance of Forni *et al.* (2005) verses Stock and Watson (2002a). They show that the mean-squared forecast errors depend on how the extracted factors are estimated and implemented in the forecasting equations. In contrast, D'Agostino and Giannone (2006) and Stock and Watson (2006) use the dataset of Stock and Watson to compare the forecasting performance of Forni *et al.* (2005) against Stock and Watson (2002a). They conclude that both methods have a similar forecasting performance even though both methods differ on how to estimate and forecast the common components.

There is a growing empirical forecasting literature that utilizes large-scale factor models to forecast key macroeconomic variables. For example, Reijer (2005) applies GDFM to quarterly Dutch data to forecast GDP growth rates. He shows that GDFM systematically outperforms and encompasses AR models only by pre-selecting an optimal subset from the whole dataset. Stavrev (2006) forecasts underlying inflation in the Euro area and observes better forecasting performance of GDFM over small-scale time series models. Similarly, Schumacher (2005) shows small forecasting improvements of GDFM over SPM. On the contrary, using quarterly Belgian data to forecast GDP growth rates, GDFM does not outperform ARAM models even after a data reduction process, where an optimal subset is chosen from the whole panel (see Van Nieuwenhuyze, 2006).

4.3 Methodology

This section gives an overview of the Generalized Dynamic Factor Model (GDFM) that is proposed by Forni *et al.* (2000, 2004, and 2005), and the Static Factor Model (SFM) proposed by Stock and Watson (2002a). Forni and Lippi (2001) illustrate the representation theory of GDFM. The technical details underlying the

GDFM are presented in appendix A. Theoretically, GDFM encompasses an *approximate* factor model of Chamberlain and Rothschild (1983) and Chamberlain (1983), in that idiosyncratic components are allowed to be weakly correlated across the panel, but the factors are static. It also generalizes the factor models of Sargent and Sim (1977) and Geweke (1977), in which the factors are dynamic, but there is no cross-correlation among idiosyncratic components at any lead and lag. This section also gives an overview of the Stock and Watson (2002a) method and illustrates its differences against GDFM. The estimation and forecasting procedures are discussed at the end of this section.

4.3.1 Forni *et al.* Method

The *i*-th time series, after suitable transformations, is a realization of real-value process from a zero-mean, wide-sense stationary process y_{it}. All y are co-stationary, where stationarity holds for the *n*-dimensional vector process $(y_{1t}, y_{2t}, ..., y_{nt})'$ for any *n*.

Formally, any given time series can be represented as the sum of two mutually orthogonal unobservable components, the common component, χ_{it}, and the idiosyncratic component, ξ_{it}:

$$y_{it} = \chi_{it} + \xi_{it} = b_i(L)\boldsymbol{u}_t + \xi_{it} \tag{1}$$

where y_{it} is a stationary process for the *i*-th time series, *i*= 1,…, *n*, at time *t*, *t* = 1,…, *T*. The common component, χ_{it}, is driven by *q* common factors (or common shocks) $\boldsymbol{u}_t = (u_{1t}, u_{2t}, ..., u_{qt})'$, e.g. a technology shock, a demand shock, an oil shock, etc. In any factor models, the number of common shocks *q* is no longer equal to the number of variables *n* [34]; $q << n$. These common shocks are loaded with different coefficients

[34] Sargent and Sims (1977), and Giannone, Reichlin and Sala (2002, and 2004) present some evidence using different datasets that few shocks are capable of explaining the dynamics of macroeconomic data.

and finite (or infinite) number of lags; that is, variables in the panel are allowed to react heterogeneously to shocks. Thus, the common component can be re-written as a dynamic linear combination of the q common shocks:

$$\chi_{it} = \sum_{j=1}^{q} b_{ij}(L) u_{jt} \tag{2}$$

The common component captures that part of the time series which comoves with the rest of macroeconomic variables. By contrast, the idiosyncratic component, ξ_{it}, is driven exclusively by variable-specific shocks such as measurement errors or variable-specific disturbances. The distinction between the common component and the idiosyncratic component has an important implication for policymakers on how to react to a shock. By identifying the source of a shock, they can decide whether to carry out local and sectoral measures, or common measures.

Rewriting the previous equations in a matrix notation:

$$\mathbf{y}_t = \boldsymbol{\chi}_t + \boldsymbol{\xi}_t = B_n(L)\mathbf{u}_t + \boldsymbol{\xi}_t \tag{3}$$

Equation (3) is GDFM[35], where $\mathbf{y}_t = (y_{1t}, y_{2t}, ..., y_{nt})'$, $n \in \mathbb{N}$ and $t \in \mathbb{Z}$, are stationary process with zero mean and finite second order moments $\boldsymbol{\Gamma}_k = \mathrm{E}[\mathbf{y}_t \mathbf{y}'_{t-k}], k \in \mathbb{Z}$, $\boldsymbol{\chi}_t = (\chi_{1t}, \chi_{2t}, ..., \chi_{nt})'$ is the common component vector, $\boldsymbol{\xi}_t = (\xi_{1t}, \xi_{2t}, ..., \xi_{nt})'$ is the idiosyncratic component vector in which its entries are orthogonal to $u_{j,t-k}$ for any $j, t, \text{and } k$. $\mathbf{B}(L) = B_0 + B_1 L + ... + B_s L^s$ is $(n \text{ x } q)$ polynomial matrix of order s in the lag operator L, whose coefficients represent the impulse response function of y_{it} to any shocks u_{jt}. Unlike SFM, the GDFM is dynamic in a sense that the common shocks are allowed to hit the series at different times. Finally, $\boldsymbol{u}_t$ is orthonormal q dimensional white noise vector, i.e. u_{jt} has a unit variance and is orthogonal to u_{st} for any $s \neq j$.

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[35] References to n will not be made explicit in $\mathbf{y}_t$, $\boldsymbol{\chi}_t$, $\boldsymbol{\xi}_t$, and $\boldsymbol{\Gamma}_k$ to avoid heavy notations. Similarly, explicit reference for T in $\boldsymbol{\Gamma}_k$ will be omitted.

Forni *et al.* (2000) impose two additional assumptions to specify the model by separating the idiosyncratic sources of variation from the common sources of variation. The first assumption allows for a limited serial and cross-sectional correlation among idiosyncratic components, which tends to zero as $i \to \infty$. That is, even though the idiosyncratic sources of variations can be shared by many series, the boundedness assumption guarantees that their effect is limited to a finite number of series. The second assumption ensures a minimum amount of cross-correlation among common components, i.e. the common shocks are present in infinitely many cross-sectional series.

The moving average representation of GDFM in equation (3) can be easily written in a static form by loading the common factors only contemporaneously. Defining $rx1$ vector as: $\mathbf{f}_t = N(L)\mathbf{u}_t = (\mathbf{u}_t, \mathbf{u}_{t\text{-}1}, \ldots, \mathbf{u}_{t\text{-}s})'$ where $N(L)$ is an r x q absolutely summable matrix function of L. The common component in (3) can be written as:

$$\boldsymbol{\chi}_t = A_n \mathbf{f}_t \tag{4}$$

where $A_n = (a_1', a_2', \ldots, a_n')' = (B_0^n, B_1^n, \ldots, B_s^n)$ is n x r matrix, and $r = q(s+1)$ is the number of static factors in $\mathbf{f}_t$. Note that r entries of $\mathbf{f}_t$ denote the *static factors*, whereas the q entries of $\mathbf{u}_t$ denote the *dynamic factors*. To be precise, u_{1t} and u_{1t-1} are two different static factors of the same common shock. Therefore, the common component is only driven by the q exogenous shocks (*dynamic factors*) and it can be expressed as a linear combination of *r static factors* of $\mathbf{f}_t$. In this model, q represents the rank of the spectral density matrix of χ, which is determined by the common sources of exogenous variation to all variables. On the other hand, r is the rank of the variance-covariance matrix of χ, which is determined by the degree of heterogeneity of the impulse response functions to the q exogenous shocks.

(i) Estimating and forecasting the common components by a one-sided filter

Since the common component and the idiosyncratic component are mutually orthogonal, Forni *et al.* (2005) argue that the forecast of any variable in the panel can be obtained as the sum of optimal linear forecasts of the common and the idiosyncratic components. Given that the latter components are weakly cross-correlated, they can be forecasted separately by a small-scale time series model such as the (AR) process.

Defining $\mathcal{G} = (\mathbf{u}, T)$ as the space spanned by the common factors, $u_{ht} = 1, ..., q$, the optimal linear h-step-ahead forecast of any common component (i.e. the minimum square error forecast) is given by:

$$\phi_{i,T+h|T} = \text{Proj}[\chi_{i,T+h} \; | \mathcal{G} = (\mathbf{u}, T)] = \sum_{j=1}^{q} \sum_{k=h}^{\infty} b_{ij,k} u_{j,T+h-k} \tag{5}$$

The GDFM relies on the spectral density of the data (i.e. dynamic covariation); therefore, the estimated common components are obtained by projecting the data onto the leads and lags of the common shocks. The unpleasant feature of the previous estimator is that $b_{ij,k}$ coefficients are based on a two-sided filter, thus making the forecasting performance deteriorate as t approaches either T or 1 (see Forni *et al.* 2000)[36]. Therefore, the common components are poorly estimated at the end of the sample since future observations are not available yet. To resolve this problem, Forni *et al.* (2005) propose an efficient procedure, which has the smallest idiosyncratic-common variance ratio and mitigates the estimation difficulties at the end of the sample, to estimate $\mathcal{G} = (\mathbf{u}, T)$ by a one-sided filter of $\mathbf{y}_t$:

$$F_{jt}^{GDFM} = \mathbf{Z}_j \mathbf{y}_t \tag{6}$$

[36] Since the projection coefficients of common components, $b_{ij}(L)$, are obtained by the inverse Fourier transform of the first q dynamic eigenvectors, those coefficients are two-sided.

where the weights $\mathbf{Z}_j$ are defined recursively as the solution of the *generalized principal component* problem:

$$\begin{aligned} \mathbf{Z}_j \quad &= \arg\max_{\mathrm{a}\in\mathbb{R}^n} \ \mathbf{a}\boldsymbol{\Gamma}_0^{\chi}\mathbf{a}' \\ \text{subjet to} \quad &\mathbf{a}\boldsymbol{\Gamma}_0^{\xi}\mathbf{a}' = 1 \\ &\mathbf{a}\boldsymbol{\Gamma}_0^{\xi}\mathbf{Z}'_m = 0 \quad \text{for } 1 \le m \le j-1 \end{aligned} \tag{7}$$

For $j = 1,....,r$; when $j = 1$ only the first constraint applies (see theorem A.2.3 of Anderson 1984). $\boldsymbol{\Gamma}_0^{\chi}$ and $\boldsymbol{\Gamma}_0^{\zeta}$ are the contemporaneous covariance matrices of the common and idiosyncratic component, respectively. The vector $\mathbf{Z}_j$ are the generalized eigenvectors of the couple of contemporaneous matrices $(\boldsymbol{\Gamma}_0^{\chi}, \boldsymbol{\Gamma}_0^{\zeta})$ and F_{jt}^{GDFM} is the *j*-th generalized principal component of $\mathbf{y}_t$. The *generalized principal component method* delivers the *r* contemporaneous linear combinations of $\mathbf{y}_t$ with the smallest idiosyncratic-common variance ratio; that is, any variable with a lower idiosyncratic-to-common variance ratio gets a higher weight.

Having obtained the *r* generalized principal components, the *h*-step-ahead forecast of any common component, based on the available information at time *T*, is the orthogonal projection of $\boldsymbol{\chi}_{T+h}$ onto the space spanned by the first *r* linear aggregate of F_{jt}^{GDFM}, for *j=1,...,r*. Formally, the estimated projection in matrix notation is given by:

$$\hat{\phi}_{T+h|T} = \hat{\boldsymbol{\chi}}_{T+h\ |T}^{GDFM} = [\boldsymbol{\Gamma}_h^{\chi}\mathbf{Z}'(\mathbf{Z}\boldsymbol{\Gamma}_0\mathbf{Z}')][\mathbf{Z}\mathbf{y}_T] \tag{8}$$

where $\mathbf{Z} = (\mathbf{Z}_1,....,\mathbf{Z}_r)'$. The contemporaneous covariance matrix of the data is denoted by $\boldsymbol{\Gamma}_0$ denotes. Therefore, the optimal *h*-step ahead forecast of $\mathbf{y}_{t+h}$ is given by the optimal linear forecast of the common and idiosyncratic component:

$$\hat{\mathbf{y}}_{t+h|t} = \hat{\boldsymbol{\chi}}_{T+h\ |T}^{GDFM} + \hat{\rho}_i(L)\boldsymbol{\xi}_{i,T} \tag{9}$$

From equation (9), it is easy to define the commonality ratio for any given time series as the ratio of the common component variance to the total variance. Therefore, the higher the commonality ratio of any key macroeconomic variable of interest, estimating and forecasting the idiosyncratic component becomes less important. Finally, since GDFM is applied on standardized data, the forecasting outcomes of equation (9) need to de-standardize; i.e. by re-attributing mean and variance.

(ii) Estimating the spectral density and the covariance matrices of the common and idiosyncratic components

Before we can estimate (8), there are some unknowns that need to be estimated, namely $\mathbf{\Gamma}_0^{\chi}$ and $\mathbf{\Gamma}_0^{\zeta}$. Forni *et al.* (2000) propose an estimation procedure that utilizes the dynamic principal component analysis (see Brillinger, 1981). Specifically, the estimated spectral density matrix of the dataset, $\mathbf{\Sigma}(\theta)$, can be decomposed into a spectral density matrix of the common component, $\mathbf{\Sigma}^{\chi}(\theta)$, and idiosyncratic component, $\mathbf{\Sigma}^{\xi}(\theta)$. Then, an inverse discrete Fourier transform is applied to the previous matrices in order to obtain the corresponding contemporaneous covariance matrices, $\mathbf{\Gamma}_0^{\chi}$ and $\mathbf{\Gamma}_0^{\zeta}$.

(iii) Selecting the number of the common and static factors

Until now, we have assumed that the number of static factors, *r*, and the number of common factors, *q*, are known. Unfortunately, there is no criteria to pre-determine *r* and *q* jointly. The information criteria proposed by Bai and Ng (2002) are utilized to determine *r*. Their information criteria determine consistently the optimal number of static factors as a trade-off between the goodness-of-fit and over-fitting of a static factor model. Concerning q, Forni *et al.* (2000) propose a decision rule to determine *q* by adding a factor at a time until the additional variance explained by the last dynamic principal component is less than a pre-specified critical value. To choose the optimal number of *q*, the eigenvalues of the dataset's spectral density matrix, $\mathbf{\Sigma}_k(\theta_h)$ for $k = 1,....,n$, have to satisfy the following two conditions:

3. The average over the frequencies θ of the first q eigenvalues diverges, whereas the average of the $(q+1)^{\text{th}}$ eigenvalues is relatively stable.

2. When $k = n$, there is a substantial difference between the explained variance of the first q^{th} principal components, and the variance explained by the $(q+1)^{\text{th}}$ principal components.

With regard to the first criteria, figure 4.1 shows the first 20 dynamic eigenvalues averaged over all frequencies. It is plotted against the number of the cross-sectional units *n*. This figure clearly shows that only the first 3 dynamic eigenvalues diverge, whereas the remaining eigenvalues are bounded.

The second criteria suggests to add one factor at a time until the additional variance explained by the last dynamic principal component is at least larger than a pre-specified critical value, e.g. 5% or 10% of the total variance. As in Altissimo *et al.* (2001), and Forni *et al.* (2000), I set the marginal explained variance at 10%. Figure 4.2 shows the percentage of variance explained by the first 10 dynamic principal components. Each of the first 3 dynamic principal components explains more than 10%. As it can be seen, the first 3 dynamic principal components together explain on average 50% of the total variance of the 83 series. Therefore, the number of common shocks that is chosen throughout the remainder of this chapter is in accordance with the previous empirical literatures such as Forni and Reichlin (1998) and Forni *et al.* (2000) find $q = 2$, Reijer (2005) and Schneider and Spitzer (2004) find $q = 3$, and Altissimo *et al.* (2001) find $q = 4$.

4.3.2 Stock and Watson Method

The difference between Stock and Watson (2002a) and Forni *et al.* (2005) is not only how the factors are estimated, but also how the forecasting procedures are implemented. Stock and Watson (2002a) estimate the common factors F_t^{SFM} as the static principal components of $\mathbf{y}_t$, that is, $F_t^{SFM} = V'\mathbf{y}_t$ where the vector V' is the static eigenvectors of the contemporaneous matrix $\mathbf{\Gamma}_0$ of $\mathbf{y}_t$. The forecast of the key macroeconomic variable of interest is then simply obtained by projecting the target variable on the estimated factors and the lags of the target variables:

$$\hat{y}_{i,T+h|T} = \hat{\alpha}_i + \hat{\beta}_i(L)\hat{F}_T^{SFM} + \hat{\gamma}_i(L)y_{i,T} \tag{10}$$

where $\hat{F}_T^{SFM}$ are the estimated factors using the Stock and Watson method. Equation (10) is the Factor Augmented Autoregressive forecasts (FAAR) or diffusion indexes forecasts as referred by Stock and Watson (2002a,b). It is easy to see that the forecasting equation of Stock and Watson (2002a), equation (10), and Forni *et al.* (2005), equation (9), are not comparable[37]. Precisely, Stock and Watson (2002a) exploit the factor structure only in the estimation stage, whereas Forni *et al.* (2005) exploit the factor structure both in the estimation and forecasting procedures.

4.3.3 Comparing Forecasting Methods

Until now, we have shown that the FAAR forecast, proposed by Stock and Watson (2002a) in equation (10), is clearly different from the non-parametric forecasts of GDFM, proposed by Forni *et al.* (2005) in equation (9). The difference between those methods is not only how the factors are estimated, but also how the forecast of key macroeconomic variables is carried out. Stock and Watson (2002a) did not impose the factor structure during the forecasting procedure, whereas Forni *et al.* (2005) adhered to the factor structure in both the estimation and forecasting step. In order to compare the efficiency gain from using either method, the forecasting equations of those two methods must have similar structure in order to be comparable. There are two different approaches to compare those methods. To make the Stock and Watson (2002a) method more comparable to the Forni *et al.*(2005) method, the estimated static factor, F_t^{SFM}, can be used to construct the non-parametric

[37] See Boivin and Ng 2005, D'Agostino and Giannone 2006, and Schumacher 2006

common component and then exploit the orthogonality assumption between the common component and idiosyncratic component to forecast each component separately. By contrast, to make the Forni *et al.* (2005) method more comparable to the Stock and Watson (2002a) method, the estimated generalized principal components, $\hat{F}_T^{GDFM}$, can be substituted in equation (10) instead of $\hat{F}_T^{SFM}$ in order to construct the corresponding FAAR forecast of the Forni *et al.* method.

If we consider the first approach, we have to analyze how the common component is estimated, since the idiosyncratic component can be estimated by a small-scale time series model. The common component of Forni *et al.* (2005) is given in equation (8), while the common component estimator of Stock and Watson (2002a) is given by:

$$\boldsymbol{\chi}_t^{SFM} = [\boldsymbol{\Gamma}_0 \mathbf{V}(\mathbf{V}\boldsymbol{\Gamma}_0\mathbf{V}')][\mathbf{V}\mathbf{y}_T] \tag{11}$$

$$\hat{\boldsymbol{\chi}}_{T+h\ |T}^{GDFM} = [\boldsymbol{\Gamma}_h^{\chi}\mathbf{Z}'(\mathbf{Z}\boldsymbol{\Gamma}_0\mathbf{Z}')][\mathbf{Z}\mathbf{y}_T] \tag{12}$$

There are few differences between (11) and (12). First, as it has been mentioned in section 4.3.2, Forni *et al.* (2005) utilize the generalized principal component method in extracting the common factors, which down-weight any variable with a large noise-to-signal ratio. Thus, the factor space $\mathbf{V}\mathbf{y}_T$ in equation (11) is estimated in a different way than the factor space $\mathbf{Z}\mathbf{y}_T$ in equation (12). Second, the common component of Stock and Watson (2002a) involves the matrix $\boldsymbol{\Gamma}_0$, whereas Forni *et al.* (2005) utilize the matrix $\boldsymbol{\Gamma}_h^{\chi}$ that effectively exploits the information contained in all lagged and contemporaneous covariance matrices of $\mathbf{y}_T$. Finally, Stock and Watson (2002a) approximate the idiosyncratic component by including lags of the dependent variable in the forecasting equation, while Forni *et al.* (2005) forecast the common component and idiosyncratic component separately by exploiting the orthogonality assumption of the two components. Therefore, to compare the non-parametric forecasts performance of GDFM against the SFM, we have to evaluate:

$$\begin{aligned} \hat{y}^{NP,SFM}_{i,T+h|T} &= \hat{\boldsymbol{\chi}}^{SFM}_{T+h\ |T} + \hat{\rho}_i(L)\boldsymbol{\xi}_{i,T} \\ \hat{y}^{NP,GDFM}_{i,T+h|T} &= \hat{\boldsymbol{\chi}}^{GDFM}_{T+h\ |T} + \hat{\rho}_i(L)\boldsymbol{\xi}_{i,T} \end{aligned} \tag{13}$$

where $\hat{\boldsymbol{\chi}}^{SFM}_{T+h\ |T}$ and $\hat{\boldsymbol{\chi}}^{GDFM}_{T+h\ |T}$ are the non-parametric common components forecast of static and dynamic factor model. The idiosyncratic components, $\boldsymbol{\xi}_t$, are forecasted separately using a small-scale time series model, namely the (AR) process[38].

If we consider the second nesting approach, then we need to assess the forecasting performance of the following two diffusion indexes forecasts:

$$\begin{aligned} \hat{y}^{FAAR,SFM}_{i,T+h|T} &= \hat{\alpha}_i + \hat{\beta}_i(L)\hat{F}^{SFM}_T + \hat{\gamma}_i(L)y_{i,T} \\ \hat{y}^{FAAR,GDFM}_{i,T+h|T} &= \hat{\alpha}_i + \hat{\beta}_i(L)\hat{F}^{GDFM}_T + \hat{\gamma}_i(L)y_{i,T} \end{aligned} \tag{14}$$

where $\hat{F}^{SFM}_T$ and $\hat{F}^{GDFM}_T$ are the estimated static and generalized factors. The lag polynomial of both $\hat{\beta}_i(L)$ and $\hat{\gamma}_i(L)$ are chosen by the Bayesian Information Criteria (BIC). Therefore, unlike the non-parametric forecasts in equation (13), neither the factor structure nor the dynamic structure is imposed in the forecasting equation (14).

Taken together, the objective is to compare the forecasting performance of both the dynamic vs. static non-parametric forecast, equation (13), and the dynamic vs. static FAAR forecasts, equation (14), across different forecasting horizons.

4.4 The GCC Area Dataset Characteristics

While there are some well-established and large databases for the U.S. and Euro areas, there is no single dataset containing a large number of macroeconomic variables for the GCC area. I devoted considerable effort to collecting

[38] The idiosyncratic component is defined as the in-sample difference between the actual data and the estimated common component.

macroeconomic variables from different sources in order to obtain a dataset that covers a wide range of economic phenomena of the GCC economies. The final database, which is quantitatively and temporally rich, can be a useful tool for future research on the GCC economies.

By including a large number of economic variables, the idiosyncratic source of variation shall be minimized simply by the process of aggregation. Since more data usually improve the statistical efficiency of estimators, this is only true for surveys in which the random sample is chosen to be representative of the population. However, Boivin and Ng (2006) use simulation and empirical examples to prove that increasing the size of the dataset beyond a certain point is not desirable. They show that factors extracted from a smaller pre-screened dataset are better than the ones extracted from a larger dataset. Therefore, the quality of the dataset is more important than the size of the dataset.

In order to construct the GCC database, I applied the same two criteria used by Altissimo *et al.* (2001) to select which variables to include in the final dataset. The first requirement is the length of the time series since the longer the time series, the more information it contained about its cyclical behavior. The other requirement is homogeneity of variables over time and across countries in order to avoid overweighting any single country in the GCC database. I collected data from different data sources such as International Financial Statistics (IFS), World Economic Outlook (WEO), Direction of Trade Statistics (DOTS), Organization for Economic Cooperation and Development (OECD), Federal Reserve Economic Data (FRED), US Department of Energy (Energy Information Administration), and the GCC Secretariat General. The final dataset consists of 83 time series with quarterly data from 1980:1 to 2007:2. It covers the major different sectors of the GCC economies. Appendix B presents a detailed list of all time series contained in the final dataset.

The economic variables contained in the final dataset are regrouped into seven homogenous groups:

- Financial variables: interest rates and exchange rates
- Price variables: consumer prices and commodity prices (real oil prices)
- Monetary variables: foreign assets and monetary aggregates
- International liquidity: total foreign reserves
- National accounts: real GDP[39]
- Foreign trade: exports and imports
- Industrial production: crude petroleum production

The final dataset underwent the following three steps in order to prepare the final dataset for the estimation stage:

4. Each time series is seasonally adjusted using the *Tramo* (Time Series Regression with ARIMA noise, Missing observation, and Outlier) and *Seats* (Signal Extraction in ARIMA Time Series) procedures proposed by Gomez and Maravall (1999). Running simultaneously, the *Tramo* procedure first estimates a regression model with possible ARIMA errors, interpolates missing values, and detects all types of outliers (i.e. additive outliers, transitory changes, and level shifts). Then the *Seats* procedure utilizes the ARIMA model to decompose each time series into unobserved components (i.e. trend cycle, seasonal, and irregular). Therefore, the outcome of the *Tramo/Seats* procedure is a time series that is free of outliers and seasonally adjusted.
5. Both the estimation of the spectral density matrix and the GDFM require each time series to be covariance stationary. To induce stationarity, the first difference of natural logarithms was taken for *Tramo/Seats* adjusted time series, with the exception of interest rates and time series with negative values where a simple first difference was taken.

[39] The quarterly data of the aggregate GCC GDP is the linear interpolation of the yearly data. As a result, the quarterly GDP data is a proxy of the unobserved GDP figures. The measurement error contained in this approximation procedure is most unlikely to be correlated with the dynamic common shocks because this measurement error only affects the GCC GDP variable. Therefore, it purged out during the estimation process of the common shocks.

6. Finally, each time series was normalized so that it has a zero sample mean and a unit variance. This procedure delivers a series that is independent of any unit of measurement. This normalization is a necessary step in order to avoid overweighting any given time series with a large variance during the estimation of the spectral density matrix. Thus, the spectral estimation is conducted on the normalized observations:

$$y_{it} = \frac{(y_{it} - \overline{y}_i)}{s_i}, \text{ where } \overline{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it} \text{ and } s_i = \frac{1}{T-1}\sum_{t=1}^{T} (y_{it} - \overline{y}_i)^2$$

4.5 Evaluating the Forecasting Performance

Various literatures compared the forecasting performance of Forni *et al.* (2005) vs. Stock and Watson (2002a); however, each used different comparison methods. For instance, Forni *et al.* (2005) compared the forecasting performance of equation (12) against (11) where in fact Stock and Watson (2002a) applied equation (10). On the other hand, Stock and Watson (2006) reported the forecasting results of equation (14) where in fact Forni *et al.* (2005) utilized equation (12). Similarly, Boivin and Ng (2005) compared the forecasting performance of equation (14) against the results of equation (12); however, they had not reported the results for equation (13). In this section, I provide a comprehensive and objective comparison of not only the dynamic vs. static non-parametric forecast, equation (13), but also of the dynamic vs. static diffusion indexes forecasts, equation (14), across different forecasting horizons.

The forecasting exercise is conducted on the real GDP growth rate and inflation rate of the GCC area. It utilized a balanced quarterly dataset of 83 time series for the period from 1980:1 until 2007:2. It simulates out-of-sample forecasts for the last 30 observations through a recursive in-sample estimation procedure. That is, beginning with a sample from 1980:1 until 1999:4, the factors are estimated, and the models are then estimated to generate the out-of-sample *h*-step-ahead forecast, $\hat{y}_{1999:4+h}$. The dataset is then updated by one quarter, 2000:1, and utilized to reestimate the factors and the model in order to generate the out-of-sample *h*-period-ahead forecasts, $\hat{y}_{2000:1+h}$. This recursive estimation procedure is reiterated 30 times , where the final sample 1980:1-2007:1 is utilized to generate only the out-of-sample 1-step-ahead forecast[40]. Finally, the forecast performance of each model is compared relative to the optimal benchmark AR(*p*) model using the Root Mean Square Errors (RMSE) statistic.

4.5.1 Dynamic vs. Static Non-Parametric Forecast

The upper panel of table 4.1 shows the forecasting performance of each method in equation (13) relative to the optimal benchmark AR(*p*) model. For the GDP growth rate, the non-parametric forecasts outperform the AR(*p*) model where the RMSE below unity for *h*=1,2. However, the forecasting performance of both methods falls as *h* increases. Furthermore, the static non-parametric forecast tends to outperform the dynamic non-parametric forecast over all horizons. In figure 4.3 and 4.4, I show the history of the GDP growth rate from 1999:4, the 1-step-ahead and 4-step-ahead out-of-sample non-parametric forecasts along with the 95% forecast interval, and the actual realizations. For comparison, I also reported in both figures the forecasting performance of the optimal AR(*p*) model. In both of these figures, the forecasts of all models closely track the movement in the GDP growth rate for *h*=1. However, the dynamic and static non-parametric forecasts are worse than the AR(*p*) model for *h*=4, since most of the realizations fall outside the 95% forecasting interval.

For the inflation rate, both the dynamic and static non-parametric forecasts do not seem to outperform the benchmark model even at *h*=1; however, the forecasting performance of both models improves as *h* increases. This last result is puzzling since the forecasting performance of any model usually falls as the forecasting horizon increases. By examining figure 4.5 and 4.6, it can be clearly seen that the non-

[40] The main advantage of using the recursive estimation method in forecasting is to assess and track the model's parameters stability in order to generate an optimal forecast.

parametric forecasts and the benchmark model appear highly accurate for h=1. On the other hand, for h=4, most of the realizations are far outside the 95% forecasting interval for the benchmark model, while they are within the forecasting interval for the non-parametric forecasts. It appears that a structural break in the inflation rate occurs around 2004:2, where it has taken a sharp upward trend. This structural break is not captured by the optimal AR(p) model. One possible explanation of why the non-parametric forecasts might be able to account for the structural break is that both the dynamic and static factor models use the covariance matrix of the whole dataset to construct the factors. Therefore, since those factors explain most of the variation in the dataset, they might be able to account for instability of the forecasting equation. By fall 2008, there was a downward inflationary pressures due to the financial crisis. Since the factor models was successful in picking up the structural break through the upward trend in inflation, it will be for future research to compare the capability of the factor models in being symmetric by identifying the structural break through the downward inflationary pressures. Furthermore, Stock and Watson (2002a) show that the estimated factors are consistent even if there is temporal parameter instability in the factor loadings.

Taking all the previous results together, the non-parametric forecasts outperform the autoregressive forecast for the GDP growth rate over the short horizon, whereas the autoregressive forecast of the inflation rate performs favorably over the short horizon. For the dynamic vs. static non-parametric forecasts, the SFM provides some efficiency gain over the GDFM across the different forecasting horizons and across the different forecasting variables. One possible explanation is that the static factor model is much easier to implement than the dynamic factor model. For the SFM, we only need to determine the number of static factors, r, to include in estimating the common component. On the other hand, in the GDFM, we need to determine many auxiliary parameters (such as q,r,M) where for most of them we have no theoretical guidelines. Another possible explanation is that the SFM might be better suited to describe the GCC area dataset than the GDFM. If the dataset at hand does not exhibit rich dynamic behavior, then the estimation of the GDFM might induce some efficiency loss.

4.5.2 Dynamic vs. Static Factor Augmented Autoregressive Forecast

The lower panel of table 4.1 shows the forecasting performance of each method in equation (14) relative to the benchmark AR(p) model. For the GDP growth rate, the FAAR forecasts greatly outperform the AR(p) model for all horizons. Unlike the non-parametric forecasts, the forecasting performance of the dynamic vs. static factors alternate across the different horizons. While the dynamic factors do well over h=1,2, the static factors perform favorably for h=4. Looking at figure 4.7 and 4.8, both the FAAR and the benchmark forecasts appear highly accurate, where the forecasts closely track the movement in the GDP growth rate for h=1,4. There is clearly an efficiency gain from using FAAR instead of a non-parametric model to forecast the GDP growth rate at 4-step-ahead. Both figure 4.4 and 4.8 show how FAAR can produce good forecasts compared to non-parametric forecasts for h=4. While most of the realizations are far outside the 95% forecasting interval for the non-parametric models, they are well within the forecasting interval for the FAAR model.

For the inflation rate, both the dynamic and static FAAR forecasts are much better than the autoregressive forecast across the different horizons. Within the two models, the dynamic factors outperform the static factors for h=1, while the static factors perform favorably over h=2, 4. Graphically, looking at figure 4.9 and 4.10, the FAAR forecasts perform well at all forecasting horizons, whereas the autoregressive forecast clearly performs worse for the forecasting horizon h=4, where most of the realizations are far outside the 95% forecasting interval. Finally, when comparing the FAAR forecasts with the corresponding non-parametric forecasts for the inflation rate, figure (6) and (10), there is a noticeably large efficiency gain from using the FAAR model over non-parametric model.

Taken together, the FAAR forecasts noticeably outperform the benchmark forecast across the different forecasting horizons. The choice between the dynamic factors vs. the static factors in the forecasting equation appears to be of less importance. When comparing the upper to the lower panel forecast in table 4.1, it is evidently clear that the FAAR forecasts outperform the non-parametric forecasts not only across the different forecasting horizons, but also across the different models. While the non-parametric models impose the factor structure in both the estimation and forecasting process, the FAAR models adhere neither to the factor nor the dynamic structure. The objective goal of the FAAR models is to examine if the factors (whether dynamic or static) have any predictive power beyond the lags of the dependent variable. That is, the FAAR models attempt to get better forecasts of the key macroeconomic variables of interest instead of getting precise estimates of the factors or the common components.

4.6 Conclusion

With the creation of the monetary union in the Gulf Cooperation Council (GCC) area, policymakers at the prospective supernational monetary agency, investment institutions, and private forecasting firms will focus on forecasting key macroeconomic variables of interest such as real GDP, consumption, investment, unemployment, interest rates, and inflation. Policymakers at the government level use those forecasts to assist them to conduct monetary and fiscal policy, while other economic agents use those forecasts to make sound economic decisions. The aim of this chapter is to generate forecasts of real GDP growth rate and inflation rate for the GCC area across different forecasting horizons. The empirical experiment is conducted on the GCC area dataset, which covers a wide range of economic phenomena of the GCC economies. The forecasting exercises attempt to compare the efficiency gain from using the dynamic factor model of Forni *et al.* (2005) versus the static factor model of Stock and Watson (2002a, b). The key difference between those two methods is not how the factors are estimated, but rather how the forecast exercise is carried out. Since those methods do not have the same structure, I have used two approaches to make them more comparable, namely a non-parametric approach and a Factor Augmented Autoregressive (FAAR) approach

The non-parametric forecasts outperform the optimal autoregressive forecast for the GDP growth rate over the short horizon, whereas the autoregressive forecast of the inflation rate performs favorably over the short horizon. For the dynamic vs. static non-parametric forecasts, the static factor model provides some efficiency gains over the dynamic factor model across the different forecasting horizons and across the different forecasting variables. The efficiency gains of the static over the dynamic factor model might be due to the fact that the latter requires many auxiliary parameters to estimate because there is no theoretical guidance to determine the optimal level of those parameters.

The forecasting performance of the FAAR models is noticeably much better than the benchmark forecast across the different forecasting horizons. The choice between the dynamic factors vs. the static factors in the forecasting equation appears to be of less importance. The forecasting performance of the FAAR forecasts systematically perform favorably compared to the non-parametric forecasts not only across the different forecasting horizons, but also across the different models. The efficiency gain of the FAAR forecasts over non-parametric forecasts can be attributed to the fact that the non-parametric models fully adhere to the factor structure in both the estimation and forecasting process, while the FAAR models adhere neither to the factor nor the dynamic structure. The ultimate objective of the FAAR models is to examine if the factors (whether dynamic or static) have any predictive power beyond the lags of the dependent variables. That is, the FAAR models attempt to get better forecasts of the key macroeconomic variables of interest instead of getting precise estimates of the factors or the common component.

Taken together, I conclude that the static factor model, whether implemented through the non-parametric or the FAAR approach, systematically performs favorably compared to the dynamic factor model. The better performance of the static factor model might be attributed to the efficiency loss induced from estimating many auxiliary parameters in the dynamic factor model, because there is no theoretical guidance to follow. Furthermore, the efficiency gain of the FAAR forecasts is substantial compared to the non-parametric forecasts. This gain can be attributed to the fact that the FAAR approach does not impose the factor structure in the forecasting step. As a result, the forecasting equation is more flexible to adapt to the dataset at hand.

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Table 4.1: Relative Out-of-Sample Root Mean Square Errors (RMSE) to the RMSE of AR Model						
	GDP			Inflation		
	h=1	*h*=2	*h*=4	*h*=1	*h*=2	*h*=4
NP (GDFM)	0.83	0.93	1.21	1.19	1.10	0.95
NP (SFM)	0.67	0.77	1.05	1.01	0.89	0.76
FAAR (GDFM)	0.63	0.60	0.72	0.64	0.65	0.80
FAAR (SFM)	0.67	0.62	0.65	0.69	0.63	0.79

NP is the non-parametric approach, FAAR is the factor augmented autoregressive approach, GDFM is the generalized dynamic factor model, and SFM is the static factor model.

Figure 4.1: Average dynamic eigenvalues over cross-sectional units

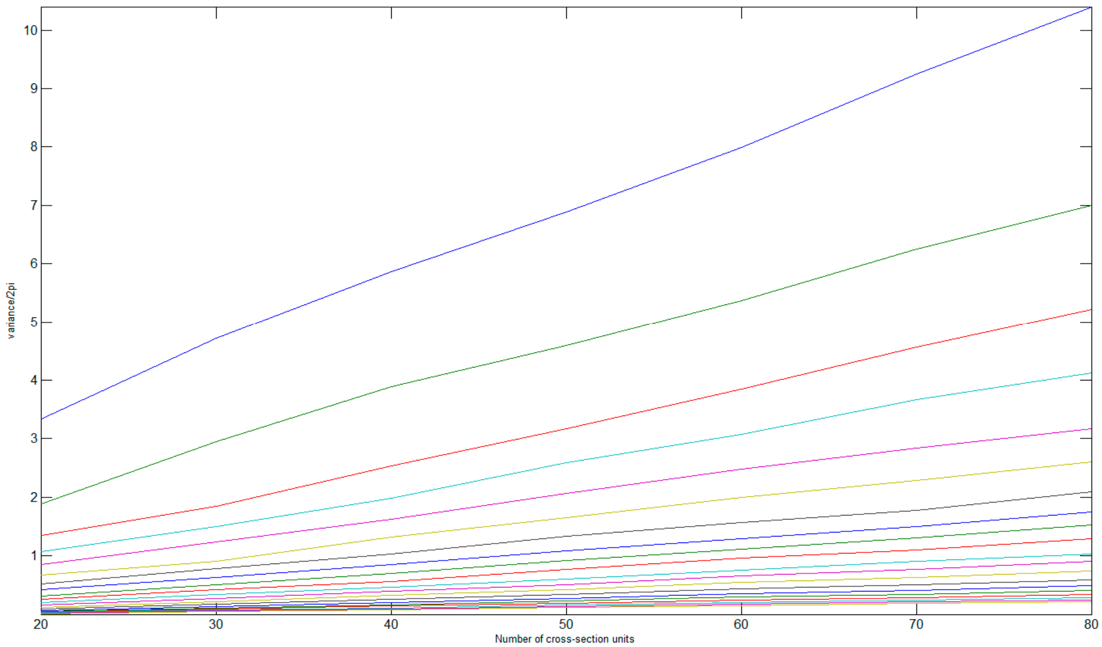


Figure 4.2: Percentage of variance explained

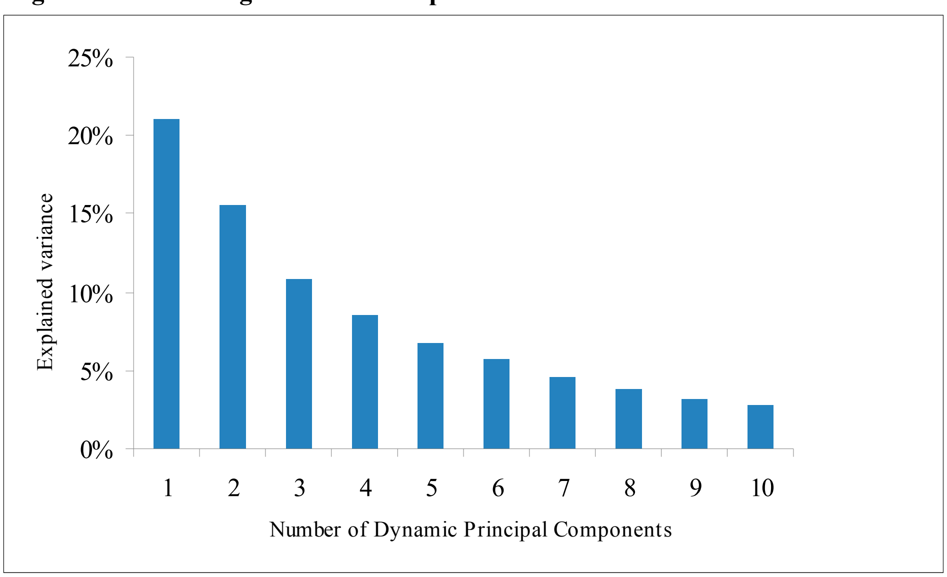


Figure 4.3: Real GDP growth rate history, 1-step-ahead forecast, and realization

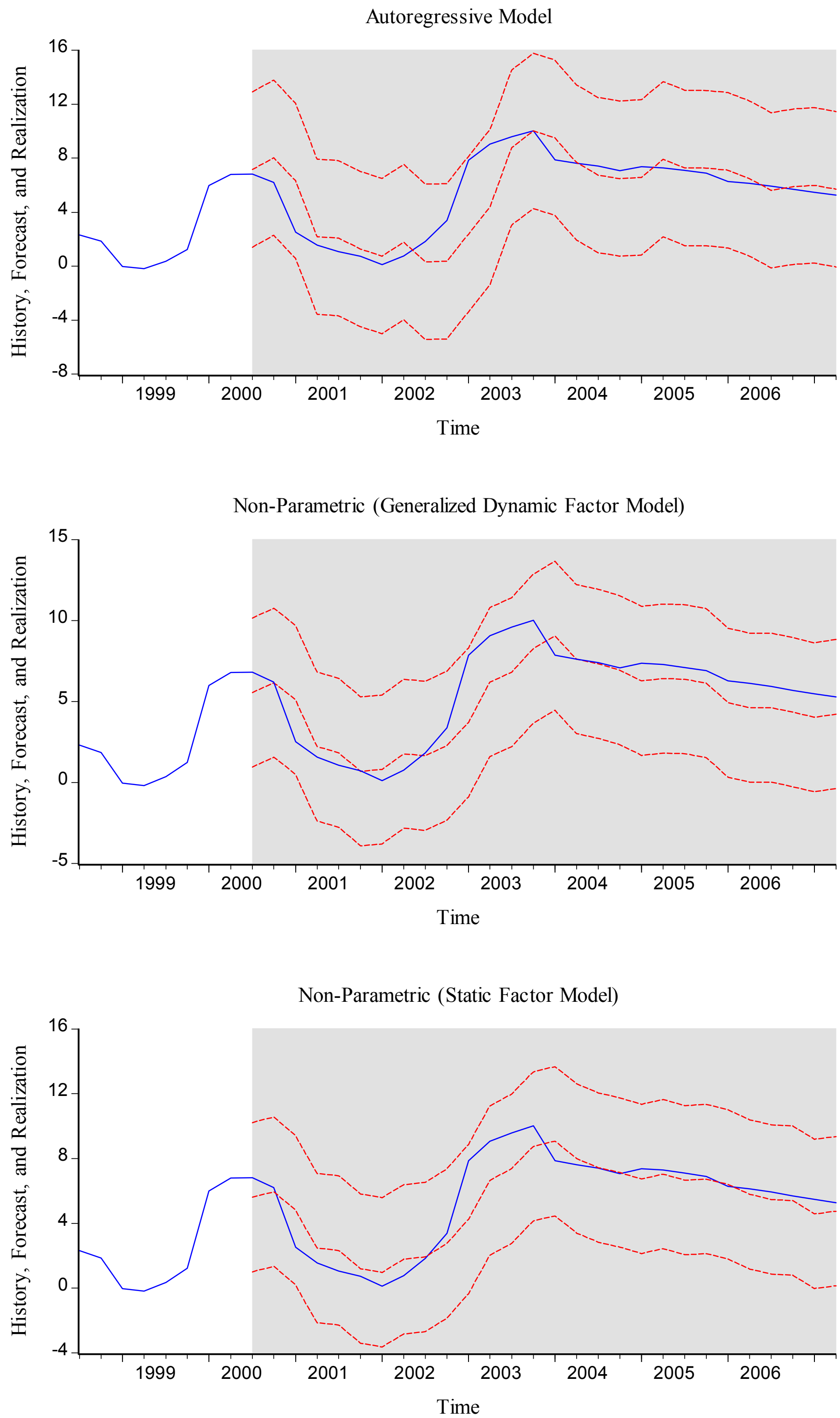


Figure 4.4: Real GDP growth rate history, 4-step-ahead forecast, and realization

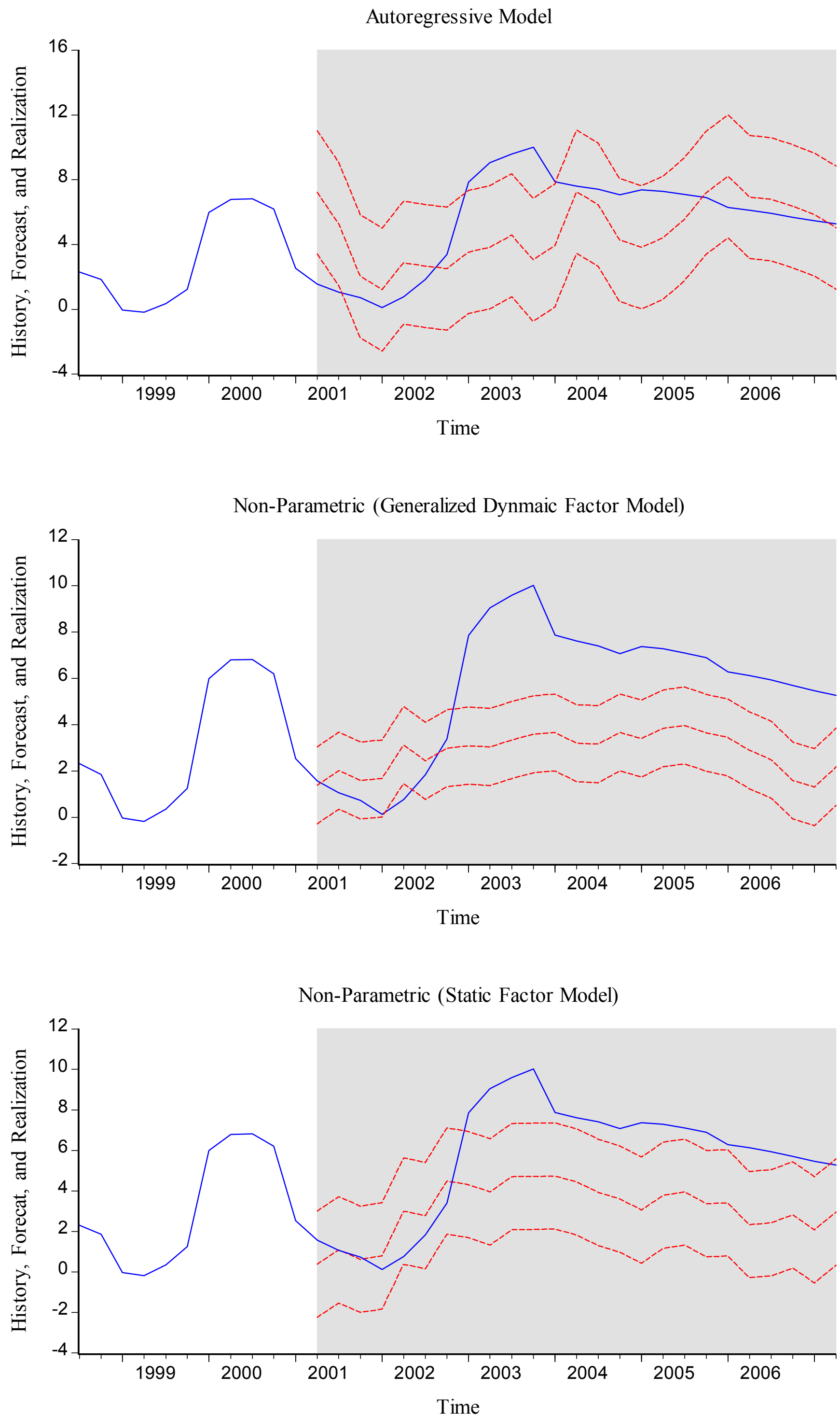


Figure 4.5: Inflation rate history, 1-step-ahead forecast, and realization

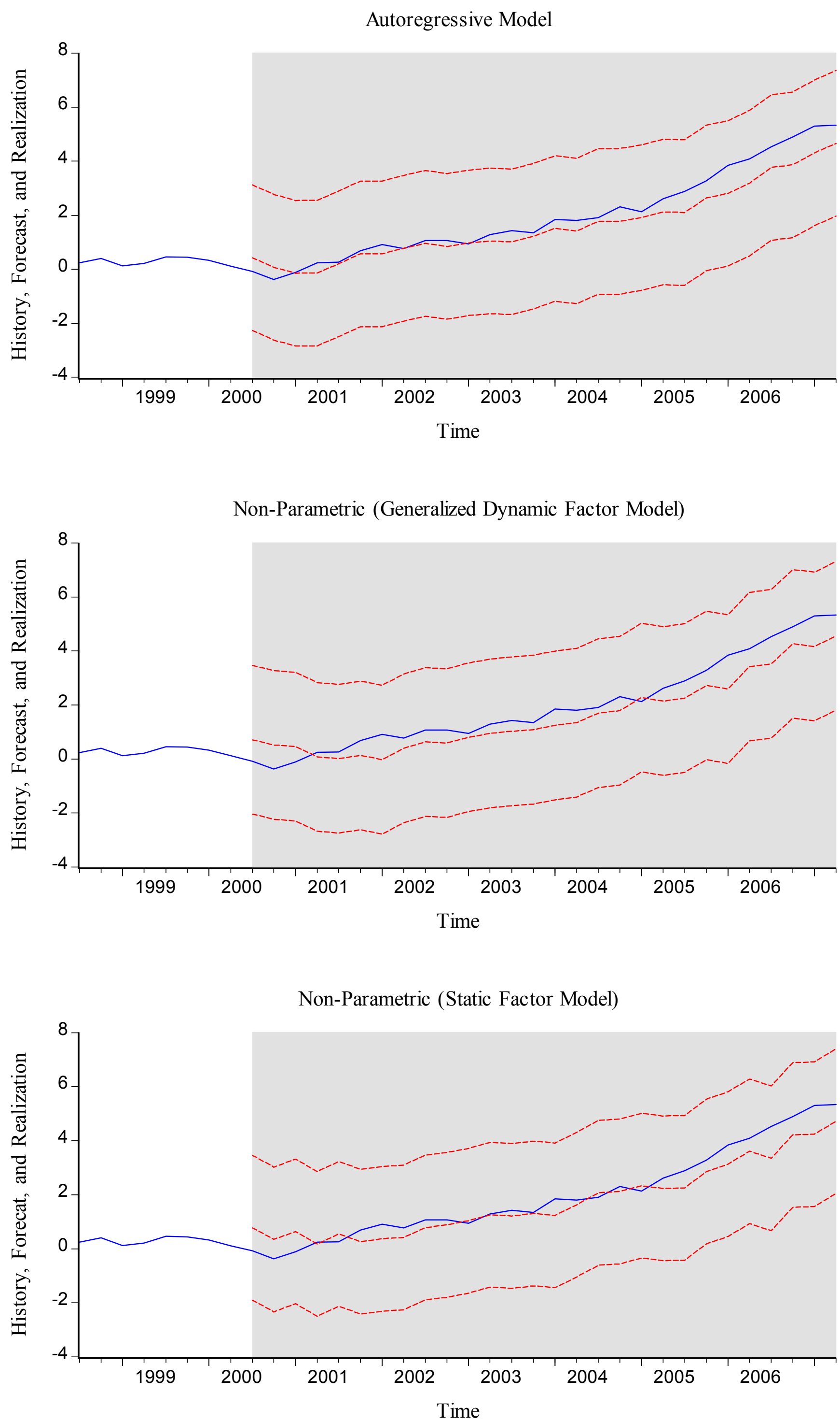


Figure 4.6: Inflation rate history, 4-step-ahead forecast, and realization

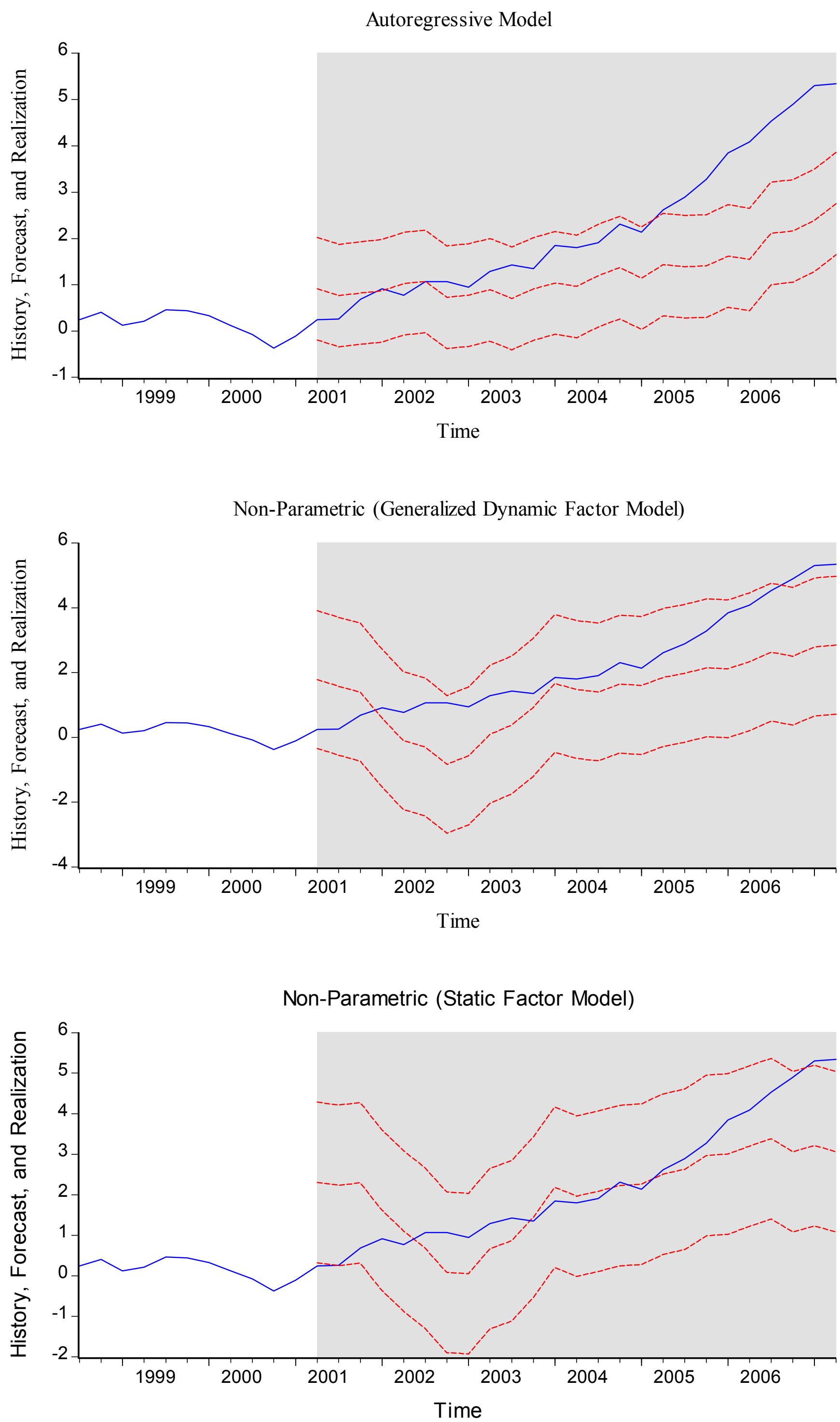


Figure 4.7: Real GDP growth rate history, 1-step-ahead forecast, and realization

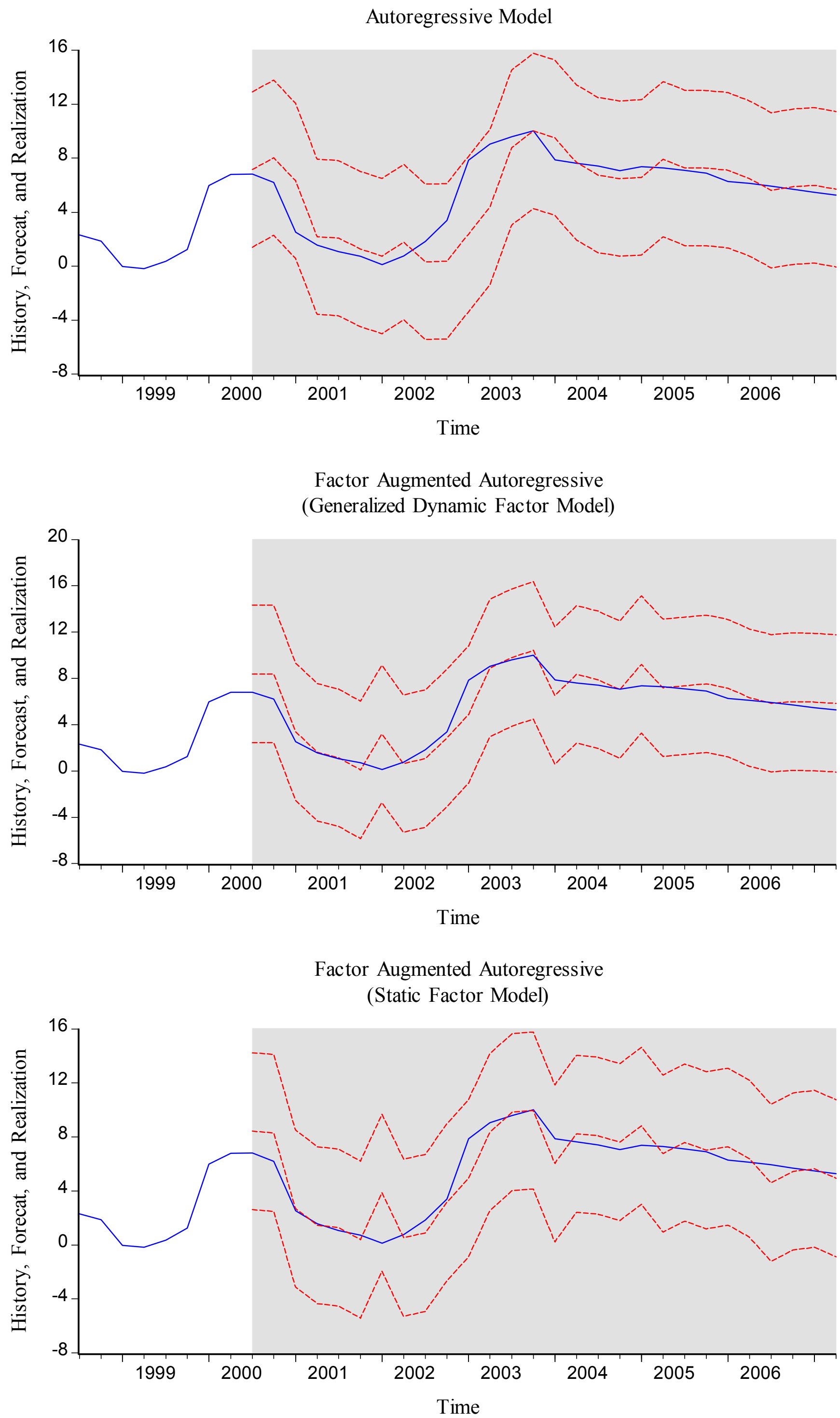


Figure 4.8: Real GDP growth rate history, 4-step-ahead forecast, and realization

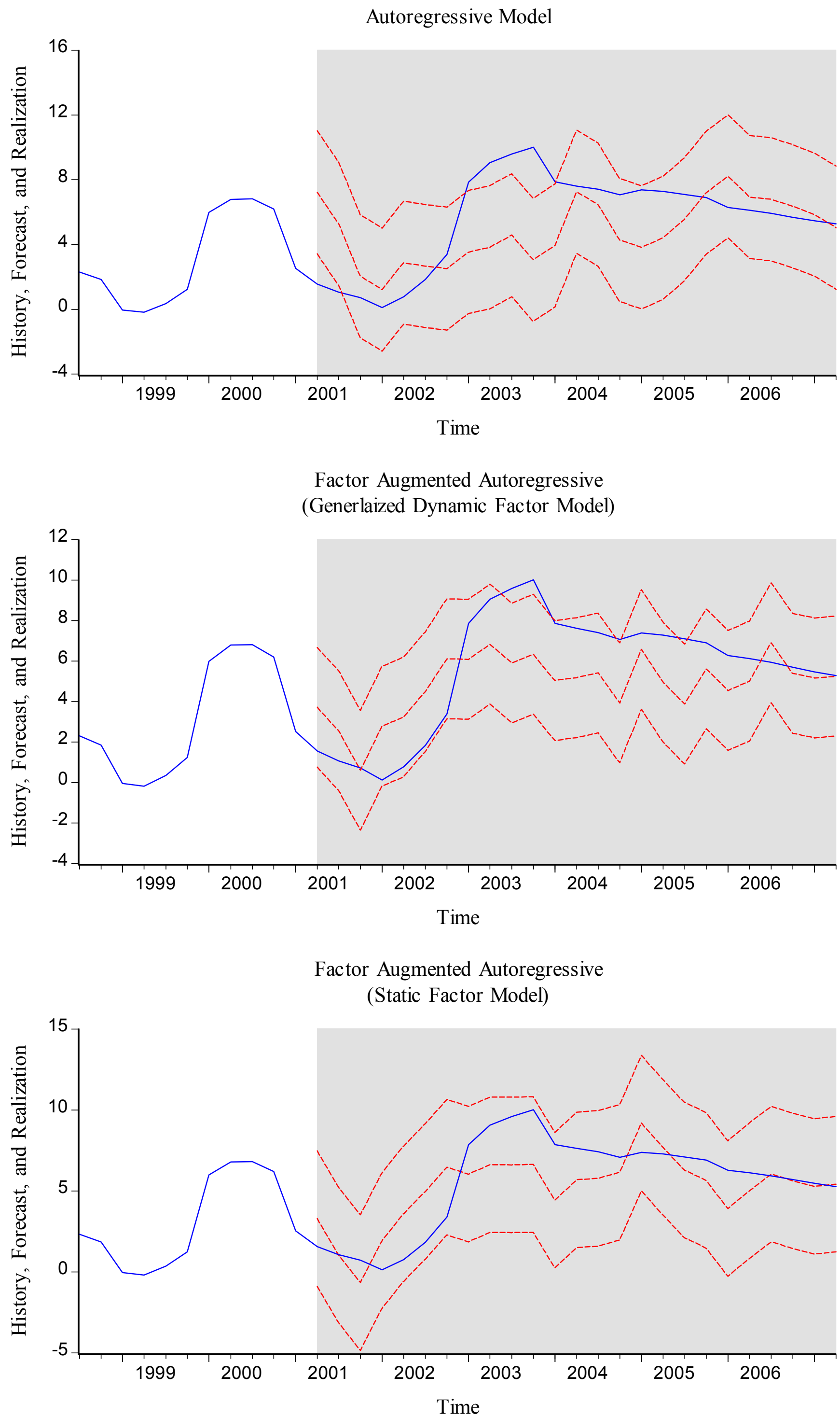


Figure 4.9: Inflation rate history, 1-step-ahead forecast, and realization

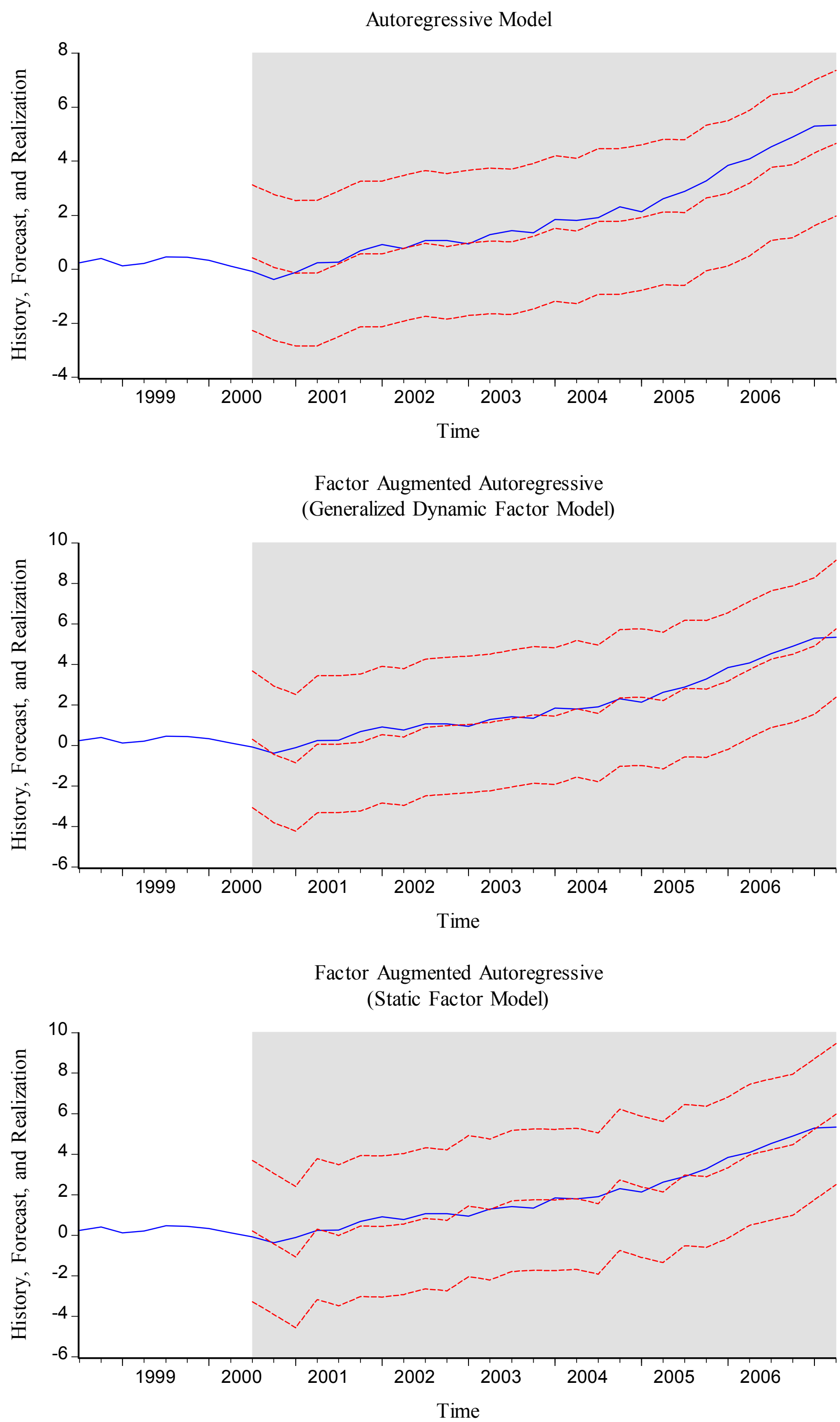
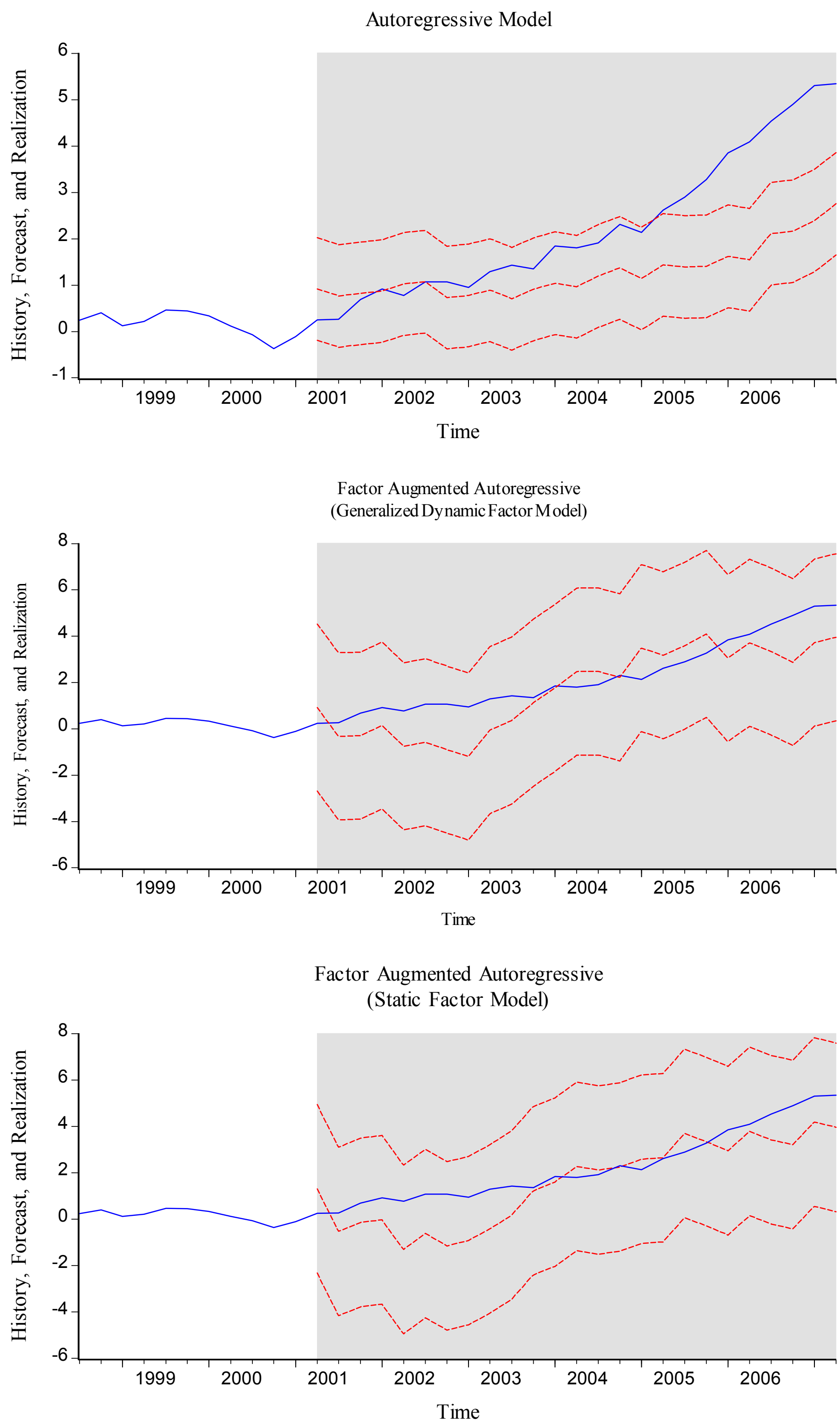


Figure 4.10: Inflation rate history, 4-step-ahead forecast, and realization



A Technical Appendix

In this appendix, I provide a brief outline of the technical details underlying the Generalized Dynamic Factor Model. First, the necessary assumptions to identify the model are presented. Second, I show how the spectral density matrix of the data can be estimated and how it is can be decomposed into two components, namely the spectral density matrices of the common and idiosyncratic components. Then, I apply an inverse Fourier transform to the previous matrices to obtain the covariance matrices of the common and idiosyncratic components. Finally, I present the one-sided estimation technique to estimate the static factors which will be used to construct and forecast the common components.

A.1 Model

Denote a double array sequence of random variables by

$$\{y_{it}, i \in \mathbb{N} \text{ and } t \in \mathbb{Z}\}$$

Any given time series can be represented as the sum of two mutually orthogonal unobservable components, the common component, χ_{it}, and the idiosyncratic component, ξ_{it}:

$$y_{it} = b_{i1}(L)u_{1t} + b_{i2}(L)u_{2t} + ... + b_{iq}(L)u_{qt} = \chi_{it} + \xi_{it} \quad \text{(A1)}$$

where y_{it} is a stationary process for the *i*-th time series, i= 1,…, n, at time t, t = 1,…, T. The common component, χ_{it}, is driven by q common factors (or common shocks) $\boldsymbol{u}_t = (u_{1t}, u_{2t}, ..., u_{qt})'$. By contrast, the idiosyncratic component, ξ_{it}, is driven exclusively by specific variable shocks such as measurement errors or variable specific disturbances. Forni *et al.* (2000) impose assumption (1) through assumption (4) to well specify the model.

Assumption (1):

(i) The q-dimensional process $\boldsymbol{u}_t = (u_{1t}, u_{2t}, ..., u_{qt})'$ is a zero-mean, orthonormal white noise vector, i.e. u_{jt} has a unit variance and is orthogonal to u_{st} for any $s \neq j$.

(ii) $\boldsymbol{\xi}_t = (\xi_{1t}, \xi_{2t}, ..., \xi_{nt})'$ is a zero-mean stationary process for any *n*, and ξ_{it} is orthogonal to $u_{j,t-k}$ for any $j, t,$ and k.

(iii) The filters $b_{ij}(L)$ are one-sided, i.e. $b_{ij}(L) = \sum_{k=0}^{\infty} b_{ijk} L^k$, and the coefficients of the filters are square summable: $\sum_{k=0}^{\infty} b_{ijk} L^k < \infty$.

Assumption (2): denote by $\boldsymbol{\Sigma}(\theta)$ the spectral density matrix of $\mathbf{y}_t$ and its entries by $\sigma_{ij}(\theta)$. Then for any $i \in \mathbb{N}$, there exists a real $c_i > 0$ such that $\sigma_{ii}(\theta) \le c_i$ for any $\theta \in [-\pi, \pi]$. This assumption implies that all $\sigma_{ij}(\theta)$ are bounded in modulus.

Assumption (3): The first idiosyncratic dynamic eigenvalues, λ_1^{ξ}, is uniformly bounded; i.e. there exists a real Λ s.t $\lambda_1^{\xi} \le \Lambda$ for any $\theta \in [-\pi, \pi]$ and any $n \in \mathbb{N}$. This assumption allows for a limited serial and cross-sectional correlation among idiosyncratic component, and tending to zero as $i \to \infty$. That is, although the idiosyncratic sources of variations can be shared by many series, the boundedness assumptions guarantee their effects are limited to a finite number of series.

Assumption (4): The first *q* common dynamic eigenvalues are unbounded almost everywhere in $[-\pi, \pi]$, i.e. $\lim_{n \to \infty} \lambda_j^{\chi}(\theta) = \infty$ for any $j \le q$. This assumption ensures a minimum amount of cross-correlation among common components. The importance of u_{jt}, for $j = 1, ..., q,$ is nondecreasing as $n \to \infty$; i.e. the common shocks are present in infinitely many cross-sectional series.

A.2 A two-step estimation method

The estimation procedures consist of two steps. In the first step, an estimate of the spectral density matrix $\boldsymbol{\Sigma}(\theta)$ of the observable $\mathbf{y}_t$ is obtained. Then, the estimated spectral density matrix can be correspondingly decomposed into spectral density matrices of the common and idiosyncratic components through the *dynamic principal component* method. To close the first step, an inverse discrete Fourier transform is applied to the estimated spectral density of the common and the idiosyncratic components to obtain the covariance matrices of the common and idiosyncratic components at all leads and lags, respectively. The second step consists of estimating the static factors using the *generalized principal component analysis*. Then, in-sample estimation and forecasting of the common components can be derived by the orthogonal projection of the common components onto the space spanned by the estimated static factors.

A.2.1 Estimating the spectral density matrices, covariance matrices, common components, and idiosyncratic components

The estimated spectral density matrix $\mathbf{\Sigma}(\theta)$ can be obtained by applying a discrete Fourier transform to the estimated covariance matrices $\mathbf{\Gamma}_k$ of $\mathbf{y}_t$. The spectral representation theorem allows us to represent the covariance matrices as a sum (integral) of elementary orthogonal periodic processes, which is fruitful for the dynamic analysis. More precisely, for some selected integer $M = M(T)$ [41], the sample covariance matrices $\mathbf{\Gamma}_k = \mathrm{E}[\mathbf{y}_t \mathbf{y}'_{t-k}]$ of $\mathbf{y}_t$ are computed with $k = -M, ..., M$ and $\mathbf{\Gamma}_{-k} = \mathbf{\Gamma}'_k$. Then, $\mathbf{\Sigma}(\theta)$ can be obtained by multiplying the sample covariance matrices by a Bartlett lag-window[42], $\omega_k = 1 - \frac{|k|}{M+1}$, and applying the discrete Fourier transform:

$$\mathbf{\Sigma}(\theta_h) = \frac{1}{2\pi} \sum_{k=-M}^{M} \omega_k \cdot \mathbf{\Gamma}_k \cdot e^{-i\theta k} \tag{A2}$$

The spectra are evaluated at $(2M+1)$ equally spaced frequencies in the interval $[-\pi, \pi]$; i.e. $\theta_h = \frac{2\pi h}{(2M+1)}$ with $h = -M, ..., M$.

The estimated spectral density matrix of the dataset $\mathbf{\Sigma}(\theta)$ can be decomposed into two orthogonal components as:

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[41] Forni *et al.* (2000) show that a fixed rule $M = M(T) = round(\sqrt{T})$ performs well in simulations.
[42] Bartlett weights are needed to avoid biases caused by the truncating the population spectral density.

$$\underbrace{\mathbf{\Sigma}(\theta)}_{\text{rank } n} = \underbrace{\mathbf{\Sigma}^{\chi}(\theta)}_{\text{rank } q} + \underbrace{\mathbf{\Sigma}^{\xi}(\theta)}_{\text{rank } n} \tag{A3}$$

The decomposition is obtained by applying the dynamic principal component analysis (see Brillinger, 1981, Chapter 9)[43]. For each frequency of the grid, the eigenvalues and eigenvectors of $\mathbf{\Sigma}(\theta_h)$ are computed. Then, by ordering the eigenvalues in descending order and collecting the corresponding eigenvectors for each frequency, we obtain the *j*-th dynamic eigenvalue $\lambda_j(\theta)$ of $\mathbf{\Sigma}(\theta)$ and the corresponding dynamic eigenvectors functions $\mathbf{p}_j(\theta) = (p_{j1}(\theta)....p_{jn}(\theta))$ for $j = 1,....,n$. The dynamic eigenvectors[44] can be expanded in Fourier series as:

$$\mathbf{p}_j(\theta) = \frac{1}{2\pi} \sum_{k=-M}^{M} [\int_{-\pi}^{\pi} \mathbf{p}_j(\theta) e^{ik\theta} d\theta]\, e^{-ik\theta} \tag{A4}$$

The dynamic eigenvectors can be rewritten in the time domain by applying an inverse Fourier transform to equation (18):

$$\underline{\mathbf{p}}_j(L) = \frac{1}{2\pi} \sum_{k=-M}^{M} [\int_{-\pi}^{\pi} \mathbf{p}_j(\theta) e^{ik\theta} d\theta]\, L^k \tag{A5}$$

The dynamic eigenvalue function $\lambda_j(\theta)$ can interpreted as the (sample) spectral density of the *j*-th dynamic principal component, $\{\underline{\mathbf{p}}_j(L)\mathbf{y}_t\}$, that is:

$$\mathbf{p}_j(\theta)\mathbf{\Sigma}(\theta)\mathbf{p}'_j(\theta) = \lambda_j(\theta) \tag{A6}$$

In analogy with the standard static principal component analysis, the contribution of the *j*-th dynamic principal component to the total variance can be represented as:

$$c_j = \frac{\int_{-\pi}^{\pi} \lambda_j(\theta) d(\theta)}{\sum_{j=1}^{n} \int_{-\pi}^{\pi} \lambda_j(\theta) d(\theta)} \tag{A7}$$

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[43] Static principal component analysis does not take into account the autocovariances, but just the covariances. Therefore, it does not maximize the variance explained.

[44] They are dynamic in the sense that they are functions of θ.

To obtain an explicit formula for $\boldsymbol{\chi}_t$, observe that the dynamic eigenvectors $\mathbf{p}_j(\theta)$ are orthonormal and the common component can be expressed as the sum of the orthogonal projection of $\mathbf{y}_t$ onto (leads and lags of) the approximate factor space spanned by each of the first *q* dynamic principal components, that is:

$$\boldsymbol{\chi}_t = [\underline{\mathbf{p}}_1'(L)\mathbf{p}_1(L) + ... + \underline{\mathbf{p}}_q'(L)\mathbf{p}_q(L)]\mathbf{y}_t \tag{A8}$$

It follows immediately that the estimated idiosyncratic component is then computed as the difference:

$$\boldsymbol{\xi}_t = \mathbf{y}_t - \boldsymbol{\chi}_t \tag{A9}$$

Similarly, the estimated spectral density matrix of the dataset $\boldsymbol{\Sigma}(\theta)$ can be decomposed into a spectral density of the common component $\boldsymbol{\Sigma}^{\chi}(\theta)$ and idiosyncratic component $\boldsymbol{\Sigma}^{\xi}(\theta)$:

$$\begin{aligned} \boldsymbol{\Sigma}^{\chi}(\theta) &= \lambda_1 \mathbf{p}_1'(\theta)\mathbf{p}_1(\theta) + ... + \lambda_{nq}\mathbf{p}_q'(\theta)\mathbf{p}_q(\theta) \\ \boldsymbol{\Sigma}^{\xi}(\theta) &= \lambda_{q+1}\mathbf{p}_{q+1}'(\theta)\mathbf{p}_{q+1}(\theta) + ... + \lambda_n \mathbf{p}_n'(\theta)\mathbf{p}_n(\theta) \end{aligned} \tag{A10}$$

Applying an inverse discrete Fourier transform to (A10) gives the estimated covariance matrices of the common and idiosyncratic component at different leads and lags:

$$\begin{aligned} \boldsymbol{\Gamma}_k^{\chi} &= \int_{-\pi}^{\pi} e^{i\theta k}\boldsymbol{\Sigma}^{x}(\theta)d\theta \\ \boldsymbol{\Gamma}_k^{\xi} &= \int_{-\pi}^{\pi} e^{i\theta k}\boldsymbol{\Sigma}^{\xi}(\theta)d\theta \end{aligned} \tag{A11}$$

A.2.2 Estimating and forecasting the common components

We cannot obtain a consistent forecast of the common components from equation (A8) since the common component estimator is a two-sided filter of $\mathbf{y}_t$. The forecasting performance deteriorates as *t* approaches *T* or 1, which is an unpleasant characteristic for forecasting. To solve this problem, Forni *et al.* (2005) propose two-step efficient estimators that retain the advantage of the dynamic approach while obtaining a consistent one-sided filter of $\mathbf{y}_t$. In the first step, they use the estimated covariance matrices (A11), which are obtained by the inverse Fourier transforms, of the common and idiosyncratic components. In the second step, they estimate the *r* contemporaneous linear combination of $\mathbf{y}_t$,with the smallest idiosyncratic-common variance ratio, as the solution of the *generalized principal component* problem. Formally, starting from the estimated covariance matrices, (A11), they compute the generalized eigenvalues μ_j ; i.e. *n* complex number solving $det(\mathbf{\Gamma}_0^{\chi} - \mu\mathbf{\Gamma}_0^{\zeta})$, and the corresponding eigenvectors $\mathbf{Z}_{nj}$ for $j = 1,....,n$; i.e. the vectors are the solution of

$$\mathbf{Z}_j\mathbf{\Gamma}_0^{\chi} = \mu_j\mathbf{Z}_j\mathbf{\Gamma}_0^{\zeta} \tag{A12}$$

and the normalizing condition

$$\mathbf{Z}_j\mathbf{\Gamma}_0^{\zeta}\mathbf{Z}_i' = \begin{matrix} 0 \text{ for } j \neq i \\ 1 \text{ for } j = i \end{matrix} \tag{A13}$$

After ordering the eigenvalues in descending order and taking the corresponding eigenvectors of the *r* largest eigenvalues, the estimated static factors are the generalized principal components:

$$F_{jt}^{GDFM} = \mathbf{Z}_j\mathbf{y}_t, j = 1,....,r \tag{A14}$$

Rewriting (A14) in the matrix notation:

$$\mathbf{F}_t^{GDFM} = \mathbf{Z}\mathbf{y}_t \tag{A15}$$

The generalized principal components deliver the *r* contemporaneous linear combinations of $\mathbf{y}_t$ which have the smallest idiosyncratic-common variance ratio. That is, a variable with a lower idiosyncratic-to-common variance gets a higher weight.

Having obtained the *r* generalized principal components, the optimal *h*-step ahead forecast of the common component based on the available information at time *t* is

$$\begin{aligned} \hat{\phi}_{T+h|T} &= \hat{\boldsymbol{\chi}}_{T+h\ |T}^{GDFM} = [\mathbf{\Gamma}_h^{\chi}\mathbf{Z}(\mathbf{Z}\mathbf{\Gamma}_0\mathbf{Z}')^{-1}][\mathbf{F}_T] \\ \hat{\phi}_{T+h|T} &= \hat{\boldsymbol{\chi}}_{T+h\ |T}^{GDFM} = [\mathbf{\Gamma}_h^{\chi}\mathbf{Z}(\mathbf{Z}\mathbf{\Gamma}_0\mathbf{Z}')^{-1}][\mathbf{Z}\mathbf{y}_T] \end{aligned} \tag{A16}$$

FHLR (2005) show that the consistency of (A16) as $(n,T) \to \infty$, i.e. $\boldsymbol{\chi}_{t+h}$ converge to the space spanned by the present and the past of $u_{1t}, u_{2t}, ..., u_{qt}$. It follows immediately that the optimal *h*-step ahead forecast of the idiosyncratic component is then computed as the difference:

$$\hat{\boldsymbol{\xi}}_{T+h|T} = \hat{\mathbf{y}}_{T+h|T} - \hat{\boldsymbol{\chi}}_{T+h|T}$$

B Dataset

Country	Descriptor
GCC	Real Gross Domestic Product
BHR	Real Gross Domestic Product
KWT	Real Gross Domestic Product
OMN	Real Gross Domestic Product
QTR	Real Gross Domestic Product
KSA	Real Gross Domestic Product
UAE	Real Gross Domestic Product
BHR	Nominal Effective Exchange Rate
OMN	Nominal Effective Exchange Rate
QTR	Nominal Effective Exchange Rate
KSA	Nominal Effective Exchange Rate
UAE	Nominal Effective Exchange Rate
GCC	Consumer Price Index 2000=100
BHR	Consumer Price Index 2000=100
KWT	Consumer Price Index 2000=100
OMN	Consumer Price Index 2000=100
QTR	Consumer Price Index 2000=100
KSA	Consumer Price Index 2000=100
UAE	Consumer Price Index 2000=100
	Average Oil Prices
BHR	Money plus Quasi-Money
KWT	Money plus Quasi-Money
OMN	Money plus Quasi-Money
QTR	Money plus Quasi-Money
KSA	Money plus Quasi-Money
UAE	Money plus Quasi-Money
BHR	Foreign Assets (Net)
KWT	Foreign Assets (Net)
OMN	Foreign Assets (Net)
QTR	Foreign Assets (Net)
KSA	Foreign Assets (Net)
UAE	Foreign Assets (Net)
BHR	Claims on Private Sector
KWT	Claims on Private Sector
OMN	Claims on Private Sector
QTR	Claims on Private Sector
KSA	Claims on Private Sector
UAE	Claims on Private Sector
BHR	Total International Reserves
KWT	Total International Reserves
OMN	Total International Reserves
QTR	Total International Reserves
KSA	Total International Reserves
UAE	Total International Reserves
BHR	Exports

KWT	Exports
Country	**Descriptor**
OMN	Exports
QTR	Exports
KSA	Exports
UAE	Exports
BHR	Imports
KWT	Imports
OMN	Imports
QTR	Imports
KSA	Imports
UAE	Imports
BHR	Crude Petroleum Production Index 2000=100
KWT	Crude Petroleum Production Index 2000=100
OMN	Crude Petroleum Production Index 2000=100
QTR	Crude Petroleum Production Index 2000=100
KSA	Crude Petroleum Production Index 2000=100
UAE	Crude Petroleum Production Index 2000=100
KWT	Oil production
QTR	Oil production
KSA	Oil production
UAE	Oil production
Japan	Real Gross Domestic Product
U.S.	Real Gross Domestic Product
EU 15	Real Gross Domestic Product
Japan	Consumer Price Index 2000=100
U.S.	Consumer Price Index 2000=100
EU 15	Consumer Price Index 2000=100
U.S.	Treasury Bill
U.S.	Government yield spread
U.S.	corporate yield spread
GCC	Deposit rate
GCC	lending rate
BHR	Claims on Central Government (Net)
KWT	Claims on Central Government (Net)
OMN	Claims on Central Government (Net)
QTR	Claims on Central Government (Net)
KSA	Claims on Central Government (Net)
UAE	Claims on Central Government (Net)

GCC is the Gulf Cooperation Council, BHR is Bahrain, KWT is Kuwait, OMN is Oman, QTR is Qatar, KSA is the Kingdom of Saudi Arabia, and UAE is the United Arab Emirates.